Chapter 2

MODELING THE PHYSIOLOGICAL AND MEDICAL EFFECTS OF EXPOSURE TO ENVIRONMENTAL EXTREMES

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INTRODUCTION

Despite a significant investment in scientific research, an age-old military problem—thermal injuries—continues to plague military operations. Scientific research can contribute to the resolution of this problem by providing military leadership, at all levels, with scientifically sound information and pragmatic guidance. The challenge is how to make scientific information gained from research accessible to the soldier in the field. One solution is to develop biomedical models. Dr James H Stuhmiller (author of Chapter 10 in this volume) believes that models are the force multiplier of research. Once developed, these models can be incorporated into information networks along with the requisite weather information, accessed via Web sites, or installed onto personal computers and PDAs (personal digital assistants) or other handheld electronic devices. Physiologically sound models can also be used in simulations that help to develop video games used as training tools for company-grade officers, junior noncommissioned officers, and medical personnel. This chapter focuses on thermoregulatory models currently in use by the US Army Research Institute of Environmental Medicine (USARIEM) as both a historical record of model development and as an indication of the promise of all biomedical modeling.

LINKING MODELS TO USERS

Biomedical models can be used to provide guidance for the deployment of forces on the battlefield. Understanding these models allows planners to better utilize scarce resources and preserve the fighting power on the battlefield, both of which can be seen as force multipliers.

The relationship between environmental parameters and the thermal status of an individual is a product of the interaction of environmental conditions, individual physical parameters (posture, body surface area, and clothing), and individual physiology (initial state, metabolic heat production, and thermoregulation). Virtually all the parameters are dynamic; hence, the universe of potential interactions is large. Despite the range of possible interactions, our perception of the thermal environment (ie, the weather) is translated into the relatively simple expectations of warmth, cold, or comfort, and some anticipation that "the weather" will have some degree of influence on our activities, ranging from essentially none (comfortable state) to severe (survival is threatened). An action plan developed in response to the anticipated conditions typically consists of a combination of clothing and thermoregulatory behavior. For example, when dangerously hot conditions exist, the unit response can be a combination of modifying uniform wear and limiting strenuous outdoor activities.

At one time, experience and common sense guided our response to potentially stressful environments. In a population that is closely linked to its environment, such as Inuit hunters, there is a shared knowledge of weather and survival. Military schools, such as jungle and mountain warfare training centers, are communicating a similar form of cultural heritage.

Today, in a more urban, mobile society, we are no longer so closely linked to our local environment, or we may be forced to operate in unfamiliar environments, so we can no longer rely on the common sense developed from experience and cultural practices for guidance. The media weather forecasts, with their emphasis on commuter weather and recommendations for proper clothing and behavior, are responding to a public need. Because military leaders may no longer have the opportunity to develop operational skills tailored for all possible environmental extremes, the military might also need the guidance equivalent to a media weather forecast. One option, originally developed primarily for military and industrial organizations, is to use thermal indices or models.

As the complexity of science and technology has increased, few individuals are able to develop full competency in areas outside their specific realm of expertise. Environmental physiology and meteorology are scientific specialties that, like any special area of study, require a good general background, plus a concentration in the area of specialization. Although it is desirable to acquire the underlying knowledge to better use and understand the limitations of their potential, models and computer systems literally bring the expertise of an environmental physiologist/biomedical modeler to the fingertips of the field medical officer.

AN INTRODUCTION TO MODELING

Biomedical models are ubiquitous. They have been developed in almost every field of medicine and science. In 2006, for example, a MEDLINE search for human models or simulations restricted to heat or cold had 11,086 hits. The number of publications in these areas indicates the interest and persistent government and commercial support for biomedical modeling and simulation. Products and software applications that incorporate biomedical models and algorithms are useful and cost effective. Modeling and simulation-based applications are numerous and include tools for planning and decision making, forecasting, and prediction. Additional applications include education and training, design and virtual prototyping, and process visualization. In scientific research, models are used for concept exploration and verification, analysis and discovery, and identification of gaps in knowledge within specific domains. Model development and use are often effective ways of gaining an improved and more detailed understanding of complex biomedical processes that cannot otherwise be obtained. In general, modeling and simulation have become a military core technology that is becoming progressively more complex as individual models are integrated into highly complex, large-scale, distributed interactive systems.[1,2]

Biomedical models use a variety of different, but often complementary, representations. They can be descriptive, graphical, analog (eg, mechanical or electronic), biological (eg, animal or cell culture models), or digital (involving use of computers and software). Models can be formulated using mathematical equations, logical symbolism, software algorithms and code, or a combination of these methods. Mathematical models are particularly useful because they are concise, and they can be solved exactly or approximated to close tolerances using iterative numerical algorithms.[3] Also, it is often possible to obtain exact equations for the sensitivity of predicted variables to perturbations in a model's coefficients and independent variables. Mathematics and formal logic provide reliable frameworks of proven rules for manipulating and evaluating modeling equations and algorithms. Consequently, analytic models can be used to verify if inferences regarding biomedical processes are logically plausible or used to derive new results that were not otherwise apparent.[4]

Complex models can be created when outputs from equations representing basic processes serve as inputs into other equations implementing feedback control mechanisms. Then, various software development tools can be used to create intricate, computer-driven realizations of the mathematical models or algorithms. Graphic user interfaces provide convenient methods for visualizing modeling results in a variety of formats, such as multidimensional charts, graphs, and tables. Model-based data can also serve as inputs to logical constructs that either discredit or help validate results and link them to computer-generated events, or to databases of advisory or cautionary messages.

There is a spectrum of model development methods.[5] At one end of the spectrum are parametric models derived using formal analytical techniques from well-defined biophysical principles. This includes mechanistic models that take advantage of concisely formulated a priori mathematical knowledge about interrelated processes. This type of model is often known as a "first principles" or "rational model." At the other end of the spectrum are essentially nonparametric models, wherein few or no a priori assumptions are or can be made regarding the most appropriate form for a system's governing equations or structure. Models based predominantly on the analysis of data sets are often referred to as empirical models. These are exemplified by models obtained by trial-and-error curve fitting. Models based on correlations and data lookup tables (coupled with simple linear interpolation between data points) are other examples of nonparametric models. Because a priori knowledge about the theory underlying a modeled process is usually not complete, models are often partly parametric or mechanistic and partly nonparametric. However, in all cases, experimental data are required for validation and to calculate the most appropriate (for the intended use) values for the coefficients.

STRATEGIES FOR FORMULATING BIOMEDICAL MODELS

The most suitable general form for the equations and logical structure of a biomedical model can often be obtained from well-established theory in the specific topic area.[6] For example, forms of equations describing the diffusion of heat in solids are derived from the basic principles and analytic expressions that describe conductive heat flow. Derivation of a model from such governing principles results in constituent equations that encapsulate the general characteristics of the heat transfer process. Experimental data, however, are required to transform the nonspecific derived equations into practical models. Obtaining specific equations from the general analytical equations requires parameter, or coefficient, estimation or identification processes. Parametric multiple regression techniques are often used to determine optimal (eg, with respect to minimum mean-squared error or maximum likelihood) values for the coefficients of a model's equations for the available data. Additional complexity and flexibility can also be built into these models by assigning parameters to the coefficients for the various levels of co-factors (eg, demographic or morphologic characteristics) that are known to be significantly associated with the response or dependent variables.

Models derived from analyses using basic biophysical principles are often at least partially represented by systems of ordinary differential equations or partial differential equations with their associated initial and boundary conditions. These techniques are invariably associated with compartmental models that describe the dynamic flux of energy between adjacent and distant volumes having different material properties.[7] Such models describe the amount of a conserved, but dynamic, substance in each compartment as functions of time. Typically, the solution of partial differential expressions is facilitated by transforming them into equivalent systems of ordinary differential equations and initial conditions. Linearization can be used to approximate the behavior of nonlinear differential systems about specified points. Such linear models can be concisely expressed using vector and matrix notation, thereby making the model's high-level structure more apparent and facilitating attempts to obtain analytic solutions.[8] Nonhomogeneous partial differential equations, however, can be difficult to solve. Often various transformations are required. Because the nature of the necessary transformations may not be apparent to those without substantial experience or training in solving nonhomogeneous partial differential equations, some expertise in mathematical modeling may be required. Time constants for outputs of a compartment model can be determined from the roots of the characteristic equation of the systems. Also, outputs will have exponential components to create predictable behavior (eg, increasing to an asymptotic or steady-state value, oscillatory, or unstable) and will extend out in time in a manner that remains valid, unlike polynomial models whose outputs are typically valid for relatively well-defined time intervals.

Alternative approaches for model development are more dependent on the evaluation of experimental data than on developing a priori mathematical constructs that represent well-established facts or assumptions regarding causative processes. Developing models directly from analysis of experimental data is the empirical, or "black box," approach. For this type of model, multiple regression techniques, including minimizing variance and statistical hypothesis testing, are typically used to select the best equations for the model, including specific values for the coefficients. The equations that result from applying this approach might have no or only fortuitous relationships to the underlying physical processes; their primary merit is that they best fit the data according to predefined criteria. Often, experienced subject matter experts will use a hybrid, or intermediate, method of model development. These modelers will usually specify from experience and descriptive theory, without formal derivations, forms (eg, sigmoidal, simple exponential, harmonic, and polynomial) for regression equations that comply with at least a high-level abstraction of underlying mechanisms and that will also result in a good fit to experimental data. Graphical visualization of the data being used for model development can assist in selecting the best form for a model's regression equation when using this intermediate model development approach. Hybrid empirical quasi-parametric model development methods used by experienced modelers and subject matter experts often result in surprisingly accurate and robust models (eg, the heat strain model developed by USARIEM) that perform as well as models derived from formal mathematical descriptions of basic biophysical and physiological processes. The present version of the USARIEM heat strain model is labeled the heat strain decision aid (HSDA).[9,10]

The black box (or purely empirical) as well as intermediate (or hybrid) model development methods result in equations that usually have a narrower range of validity than those derived from basic principles. The black box method results in equations that can be trusted to reliably predict responses for only a limited range of the independent variables, usually the approximate limits of the original data set.

Thus, an application of an empirical or hybrid model beyond the scope of the original conditions is of uncertain validity. For example, data from a study evaluating a process known to cause asymptotic responses can be seemingly well-modeled, along limited intervals of the independent variables, by linear or polynomial functions. However, extrapolating significantly beyond the range of the independent variable used in the studies from which the data were obtained would soon result in large errors, as the response predicted by the polynomial functions and actual asymptotic data increasingly diverged. Because equations in an empirical model typically do not represent actual processes, their selected forms primarily illustrate convenient mathematical representations that approximate experimental or observational data to specified tolerances. In contrast, the equations and terms in analytically derived models usually can be expanded to cover a broader range of phenomena, provided those conditions represent a series of similar mechanistic relationships. The coefficients and intermediate output values from such algorithms allow for state-space representation, with state variables that might be fully observable and measurable in the corresponding real system.

A HISTORICAL OVERVIEW OF THERMAL MODELS AND INDICES

Indices vs Models

When the mathematical model results are expressed as a single value, and interpreted or indexed with a reference scale rather than used directly, the model is referred to as an index. For example, the original windchill index (WCI) values[11] had to be interpreted according to a range provided by the authors. As computers have become more accessible, there is a diminished appeal for expressing modeling results as indices. Users are beginning to realize that more sophisticated predictions and guidance are just as accessible as simple indices. For example, versions of the USARIEM heat strain model[12,13] directly predict tolerance times, water needs, and / or changes in rectal temperature or heart rate. At present, a transition from indices to more detailed models is occurring despite the persistence of older indices such as wet bulb globe temperature (WBGT)[14] and new indices such as the environmental stress index.[15]

Equivalent Temperatures

The use of a single environmental parameter to categorize the overall thermal environment is a convention followed by most individuals. Actual environmental conditions can be a combination of temperature, wind, radiation, and humidity, but it is more convenient just to say it will be "in the 70s" (°F). We can refer to the effects of high and low temperatures on human physiology when in fact we are referring to thermal environments that represent a strong potential for either heat gain (hot environments) or heat loss (cold environments) between the environment and the body. As noted previously, the thermal environment is the product of four parameters. To visualize the interaction of those parameters would require a four-dimensional space. In any discussion of the thermal environment, it would be much easier if we could use only one parameter instead of four, and temperature is the most easily measured and conceptualized environmental parameter.

Characterizing the net effect of the thermal environment on heat exchange in the units of temperature is the basic premise behind equivalent temperatures. A given combination of all four parameters is equivalent to an air temperature that is higher, lower, or equal to the measured air temperature. Thus, a windchill temperature is usually lower than air temperature; and, on a warm, humid day, the equivalent temperature is higher than the measured air temperature. One problem has been that, when the actual conditions are milder than normal or standard conditions, the equivalent temperature is also milder than the measured temperature. These phenomena result from assumptions inherent in the equations, such as assuming that an individual is walking at a fixed rate, and hence a "calm" state includes some convective transfer. Weather forecasters might not have much trouble convincing people that, because of a strong wind, the temperature at –20°C is actually "colder" than the –20°C value the thermometer reads. However, people are less likely to believe that, if wind speed is less than normal, the temperature is less than –20°C.

In indoor office studies, where air velocity is usually a low, constant value, humidity is low because of central heating or air conditioning; the mean radiant temperature is near air temperature, thus using only air temperature to represent environmental variability is often accurate. To adjust the comfort level, the temperature setting of the thermostat should be adjusted. That action can, in fact, alter all four parameters, but the most noticeable change is in air temperature. In a room with an indoor swimming pool, the large water surface area of the pool virtually ensures a saturated relative humidity of 100%. In that environment, an air temperature that differs from the office temperature would have the same effect on comfort or thermal state. If the office environment is identified as the standard environment, the equivalent temperature in the pool room would be the air temperature required to achieve the same standard of comfort or thermal state. It is important also to identify the standard for equivalency, because thermal balance and comfort are not always achieved in the same thermal environment. It should be noted that thermal balance is dependent on an individual's activity and clothing. Equivalent temperatures generally assume equivalent clothing and metabolic rates. A principal shortcoming of all of these instruments (ie, WBGT, the Oxford index, and WCI) is that metabolic rate and clothing are ignored. Those indices, as originally presented, are environmental rather than physiological indices, because they are not scaled for differences in metabolism and clothing.

General Environmental Indices

An example of a general environmental index is operative temperature.[16–18] The original concept of operative temperature was to calculate a single value, expressed as a temperature, that would account for heat exchange by convection and radiation, if all temperatures were at the same operative temperature. Operative temperatures and the derivative new effective temperature (ET*) and standard effective temperature models are discussed in detail in Chapter 8 to illustrate the integration of weather and biophysics into a biomedical model.

Indices for Heat Exposure

Not surprisingly, there are many different indices for calculating heat exposure. These include the following:

- ET,
- WBGT,
- weather service indices based on temperature humidity,
- the Oxford (wet-dry) index (WDI),
- the predicted 4-hour sweat rate (P4SR),
- the required sweat rate (S_{req}), and
- ET*.

Effective Temperature

ET is an index based on wet bulb (T_{wb}) and dry bulb (T_a) air temperatures and air velocity (u), which associates actual conditions to equivalent still air, saturated (100% relative humidity) conditions. It originated as a comfort index,[19] but was modified to index physiological strain.[20] ET is often represented as a nomogram (Figure 2-1), which is similar to a psychrometric chart. Corrected ET (CET)[21] substituted globe temperature (T_{bg}) for T_a. The basic criticisms of ET and CET are that the indices are based on light or sedentary activity, and they cannot be adjusted for metabolic activity. Only two levels of clothing—(1) nude and (2) light, indoor clothing—were included in the original scales. In common with other indices, later research has provided some guidance for adjusting ET and CET for different metabolic rates. For example, Lind[22] has calculated that CET upper limits ranging from 30.2°C to 26.9°C for different work levels correspond to metabolic rates of 209 to 488 W. An additional criticism is that the original derivation of ET was based on initial or transitory sensations; therefore, it is not as useful for predicting responses during a prolonged exposure. ET and CET are also considered appropriate for only moderately warm climates, rather than extreme environments. The basic concept of ET has been modified several times to eliminate these criticisms. ET and CET have gradually been replaced by newer measures of heat stress, such as ET* and standard ET, which are discussed in Chapter 8.

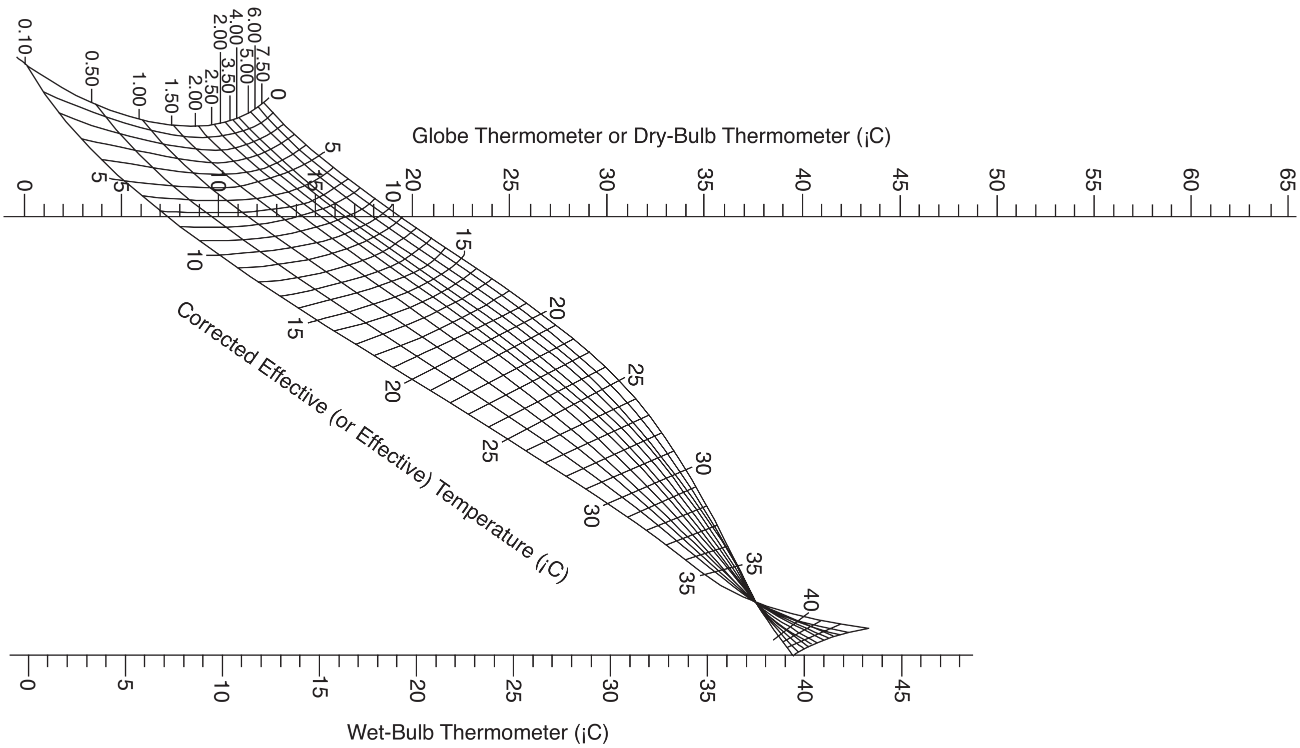

Fig. 2-1. Nomogram for corrected effective temperature for light, indoor clothing.
Illustration: Adapted with permission from Ellis FP, Smith FE, Walters JD. Measurement of environmental warmth in SI units. *Br J Ind Med.* 1972;29:361–377.

Wet Bulb Global Temperature Index

The WBGT index has been described[23] as an effort to simplify an earlier climatic index (ET). To establish the WBGT, three temperature sensors—(1) a shielded dry bulb thermometer to measure T_a; (2) a "naturally aspirated" wet bulb thermometer to measure primarily humidity (T_{nwb}); and (3) a 15-cm (6-in.) Vernon black globe thermometer (T_{bg}) to measure the combined effect of wind speed, air temperature, and radiation—are used to calculate indoor and outdoor WBGT values. These values are interpreted according to guidance provided by Yaglou and Minard[24] and later researchers. The equations for indoor and outdoor WBGTs are:

(1) $0.7T_{nwb} + 0.2T_{bg} + 0.1T_a$ [outdoors, °C or °F]
(2) $0.7T_{nwb} + 0.3T_{bg}$ [indoors, °C or °F].

Indoors, without significant drafts or radiation sources, the assumption is sometimes made that the black globe temperature is the same as the ambient temperature.[25] Botsford[26] discusses other equations for WBGT. The original empirical scale was developed to provide guidance for the training of acclimatized and unacclimatized military personnel. Application of the original equation is limited by the original database; fit, young US Marines in a summer military uniform engaged in moderately intensive exercise. WBGT is a simple index that uses simple sensors and minimal calculations. WBGT is not recommended for conditions with high humidity.[27] It has been widely used by the military, particularly in the United States. Adjustments to WBGT have been made for different work rates and clothing. Sources for guidance include the US Army's *Technical Bulletin 507* on the prevention, treatment, and control of heat injury,[14] the National Institute for Occupational Safety and Health recommended standards for exposure to hot environments,[28] the American Conference of Government Industrial Hygiene handbook,[29] and the International Standards Organisation guideline 7243.[30]

Weather Service Indices Based on Temperature Humidity

The US National Weather Service (NWS) uses a temperature-humidity index (HI) derived from Steadman's heat index. The NWS approach was to generate a fourth-order polynomial using only air temperature (T_F in °F) and percent relative humidity from Steadman's model[31,32] for apparent temperature.[33] The rationale for developing the derived equation for HI was to save computation time and computer resources. The lowest thresholds for HI are possible fatigue, with prolonged activity beginning at HI = 80°F, and an increasing potential for heat injury—defined as "sunstroke," heat cramps, or heat exhaustion—at 90°F to 105°F. Those injuries become likely between 105°F and 130°F, with a potential for heatstroke; when HI ≥ 130°F, heatstroke is highly likely.

A similar temperature-HI (Humidex [HD])[34,35] is used by Meteorological Services Canada. The input variables are T_a (°C) and a different variable for humidity, T_{dp} (°C). Critical values for HD are ≤ 29°C and are comfortable; discomfort begins at 30°C, and a majority of individuals should be uncomfortable when HD reaches 40°C. At HD ≥ 46°C, some activity restrictions are merited.

In 2001, the US and Canadian weather services worked together to adopt a new way of calculating windchill temperature. The working group was also tasked with considering a common HI rather than HI in °F and HD in °C, and different scales for interpretation. To make a comparison between the two indices, a USARIEM mathematical model was run with constant values for all parameters except T_a and humidity to calculate core temperature (T_c). By setting most of the inputs as constants, the model was essentially converted into a temperature-HI. The model T_c values were plotted against the respective HI or HD index values calculated for different combinations of temperature and humidity. The results indicated a linear relationship between HI and predicted T_c, and an exponential relationship for HD and T_c.[35]

Oxford Index

Lind et al[36] developed the Oxford index (also known as the WDI) from data on mine rescue workers.[23,37] Weighted values of T_a and T_{wb} are used to calculate WDI. There are no specific corrections for radiation, wind speed, clothing, or metabolic rate in the equation. WDI is most appropriate for environments similar to mines. McIntyre[37] cites later work to calculate safe tolerance times for different metabolic rates. Eissing[38] classifies WDI as a climatic index based on algebraic combinations of climatic parameters and cites several additional examples. Of Eissing's listed indices, the Belgian ET[39] was virtually identical to the WDI. A similar index for military chemical protective clothing, the heat-HI[40] (HHI) uses an equal weighting of T_a and T_{wb} (HHI = $0.5\ T_a + 0.5\ T_{wb}$) to derive a value that is interpreted using the WBGT index scale. Bell and colleagues[41] proposed a basic equation of

$$T = p \bullet T_{wb} + (1 - p) \bullet T_a$$

and presented different p values for sitting (0.12), standing (0.05), and working (0.10). Gagge and Nishi[42] used $0.7\ T_{wb} + 0.3\ T_a$ for indoor WBGT.

Predicted Four-Hour Sweat Rate

The P4SR[43] is also based on the assumption that sweat can be equated to the level of physiological strain. The P4SR is based on an empirical derivation of the relationship between the observed responses (sweat rate) of subjects and environmental stress. The authors assumed a maximum sweat rate of 5 liters in a 4-hour period. If the P4SR is less than 4.5 liters, it is assumed that a healthy young population would not experience heat-related injuries. To use the equation, values for T_a, T_{wb}, T_{bg}, wind, and metabolism are used to derive a basic 4-hour sweat rate from a nomogram (Figure 2-2) similar to a psychrometric chart. A second equation is then used to calculate the P4SR based on clothing and metabolic rate. The original P4SR was based on only two clothing conditions. McIntyre[37] indicated that, whereas the P4SR value increases when clothing insulation (and clothing amount) increases, in reality, actual sweat loss would decrease. Another criticism is that the index applies only to acclimatized subjects.

Required Sweat Rate

Required sweat rate (S_{req}), ISO 7933 (1989),[44] is a rationally derived index based on a calculation of the sweat required to maintain thermal equilibrium. Vogt and colleagues[45] cite Givoni's index of thermal stress as the theoretical basis for S_{req}. However, to determine S_{req}, in place of Givoni's empirically derived estimates, heat exchange coefficients are used to calculate terms in the heat balance equations. Consequently, S_{req} is more of a modernization of Belding and Hatch's heat stress index. Required environmental inputs are values for T_a, T_r, v, and P_a (ambient water vapor

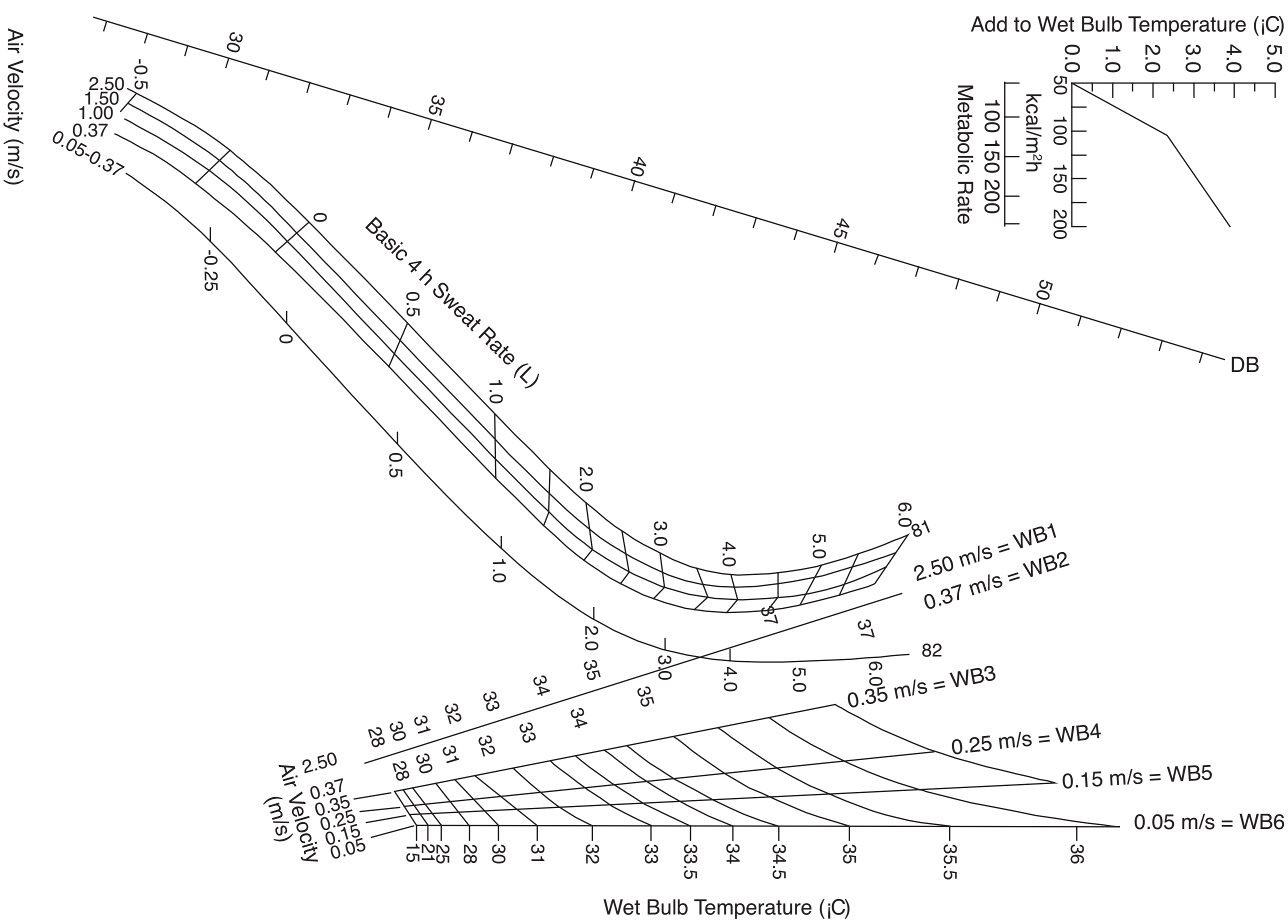

Fig. 2-2. Nomogram for the predicted 4-hour sweat rate.
WB: wet bulb.
Illustration: Adapted with permission from Ellis FP, Smith FE, Walters JD. Measurement of environmental warmth in SI units. *Br J Ind Med*. 1972;29:361–377.

pressure). Clothing factors are represented by R_e (a term for clothing vapor permeability resistance) and I_{cl}. ISO 9920[46] presents methods for estimating I_{cl} and R_e. Methods are presented for deriving or estimating other clothing parameters, mean skin temperature ($\bar{T}_{sk}$), and M (or metabolic heat production). A term for sweating efficiency was adopted because not all sweat produced contributes to evaporative cooling. S_{req} is the basis for ISO 7933.[44] Parsons[47] presents the equations and regression relationships for calculating S_{req} as it is presented in ISO 7933.[44] Allowable exposure times, or duration-limited exposures (DLEs), are based on either heat storage (DLE1) or water depletion (DLE2) for a maximum 8-hour shift.

Indices for Cold Exposure

Windchill is a concept that has been used by both the military and civilian sectors for a considerable period of time. This section will discuss the evolution of the concept, as well as ways to prevent cold injury by identifying adequate levels of clothing insulation.

Windchill Index and Windchill Temperature

By far, the most widely recognized index for cold weather exposure is the WCI.[11] It is based on the intuitive relationship between heat loss or chilling and increasing wind speeds. The WCI was an effort to calculate an index number for the cooling rate of wind and air temperature on bare skin. The authors of the index recognized that solar effects were neglected, and the index does not relate to clothing or a high activity level.

The idea of a windchill equivalent temperature (WCET) is based on the same assumptions as other equivalent or standard temperatures.[48] WCET is the same combination of wind speed and air temperature that results in the same WCI as still air. However, equivalent temperatures are based on the assumption of a minimal wind speed of 4 mph (1.8 m • s^{-1}).

Shortly after the introduction of WCI, criticisms began.[49] The flaws in WCI, especially the derivative WCET, were known for more than 50 years. As noted previously, even the authors[11] identified some limitations of their index in the original publication. In 2000, a US and Canadian Joint Action Group for Thermal Indices, sponsored by the Office of the Federal Coordinator for Meteorological Services and Supporting Research,[50] undertook an effort to develop a new windchill model.[50–52] The principal modelers were Osczevski[53] and Bluestein and Zecher.[54] A team of researchers at Defence Research and Development Canada (in Toronto [DRDC Toronto])

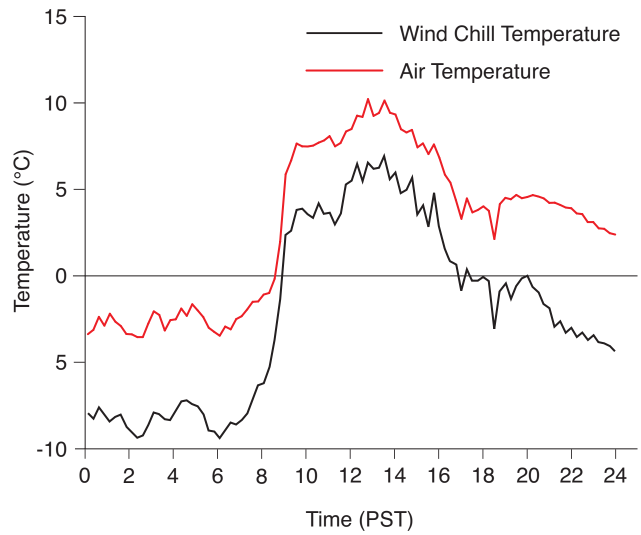

Fig. 2-3. Comparison of air temperature and windchill equivalent temperatures at the US Marine Corps Mountain Warfare Training Center, January 27, 1988. Frostbite from wind exposure cannot occur above 0°C.
PST: Pacific Standard Time

conducted human testing that supported the modeling effort.[55] In a situation parallel to the derivation of the NWS predictive equation for HI, the original iterative program required too great an allocation of computing resources. Thus, simplified equations in metric and English units were developed to predict the new windchill temperature (WCT). Figure 2-3 illustrates the relationship between T_a and WCT. Figure 2-4 presents the revised WCT values for different combinations of T_a and wind speed. The metric WCT equation is:

(3) $$WCT = 13.12 + 0.6215T_a - 11.37V^{0.16} + 0.3965T_aV^{0.16}\ [°C]$$

V is the wind velocity in kilometers per hour (kph) measured at 10 m. To use the chart for a ground-level wind speed, multiply the ground wind velocity by 1.5. In addition, an equation to predict the time for freezing of the exposed skin on the face was developed. The shading on Figure 2-4 represents various calculated time intervals to facial frostbite. The equation that calculates time to facial frostbite is based on assumptions concerning the insulation of human skin that, in turn, varied with the age of the subjects. A revised equation for predicting time to frostbite for exposed faces was developed by Tikuisis and Osczevski.[56,57] Thus, the values in the WCT table—especially the values for time to frostbite—should be considered advisory rather than absolute.

Temperature (°F)

Wind (mph) \ Calm	40	35	30	25	20	15	10	5	0	-5	-10	-15	-20	-25	-30	-35	-40	-45
5	36	31	25	19	13	7	1	-5	-11	-16	-22	-28	-34	-40	-46	-52	-57	-63
10	34	27	21	15	9	3	-4	-10	-16	-22	-28	-35	-41	-47	-53	-59	-66	-72
15	32	25	19	13	6	0	-7	-13	-19	-26	-32	-39	-45	-51	-58	-64	-71	-77
20	30	24	17	11	4	-2	-9	-15	-22	-29	-35	-42	-48	-55	-61	-68	-74	-81
25	29	23	16	9	3	-4	-11	-17	-24	-31	-37	-44	-51	-58	-64	-71	-78	-84
30	28	22	15	8	1	-5	-12	-19	-26	-33	-39	-46	-53	-60	-67	-73	-80	-87
35	28	21	14	7	0	-7	-14	-21	-27	-34	-41	-48	-55	-62	-69	-76	-82	-89
40	27	20	13	6	-1	-8	-15	-22	-29	-36	-43	-50	-57	-64	-71	-78	-84	-91
45	26	19	12	5	-2	-9	-16	-23	-30	-37	-44	-51	-58	-65	-72	-79	-86	-93
50	26	19	12	4	-3	-10	-17	-24	-31	-38	-45	-52	-60	-67	-74	-81	-88	-95
55	25	18	11	4	-3	-11	-18	-25	-32	-39	-46	-54	-61	-68	-75	-82	-89	-97
60	25	17	10	3	-4	-11	-19	-26	-33	-40	-48	-55	-62	-69	-76	-84	-91	-98

Frostbite Times 30 minutes 10 minutes 5 minutes

$$\text{Windchill (°F)} = 35.74 + 0.6215T - 35.75(V^{0.16}) + 0.4275T(V^{0.16})$$

Where T = Air Temperature (°F) V = Wind Speed (mph) *Effective 11/01/01*

Fig. 2-4. National Weather Service windchill calculation chart.
Illustration: Reproduced with permission from the National Oceanic and Atmospheric Administration (NOAA). http://www.nws.noaa.gov/om/windchill/index.shtml. Accessed May 24, 2007.

As presently used, WCT is related to the danger of frostbite on bare skin. Among the most direct criticisms of windchill is the fact that a simple wind barrier (clothing or shelter) rapidly negates the effect of high wind speeds, but the "equivalent" combination of extreme low temperatures and low wind speed cannot be readily alleviated by clothing or a simple shelter. A calm day with an air temperature of –40°C is always dangerous, whereas an equivalent WCT of –40°C for a combination of –25°C (–13°F) T_a and 35 kph at 10 m (6.5 m • s^{-1} at ground level) wind speed does not pose a great danger to an experienced or well-informed individual with adequate clothing or shelter. The difference is best demonstrated by using the example of an individual stranded inside an automobile. Eventually, the interior of the car may cool to the outdoor air temperature, but no matter how strong the wind blows, the interior of the car will never become colder than air temperature. The only direct effect wind speed will have on the interior temperature will be on the rate or time that it takes to cool it down to the outside air temperature.

Most windchill tables suggest that there will be little danger of frostbite above an air temperature of –10°C, regardless of the wind speed. For the face, which has enhanced circulation, this might be true. However, the situation is more complex. Military epidemiology from World War II[58] indicates that frostbite injuries appear when the air temperature goes below 0°C. The incidence of frostbite on other parts of the body, especially from contact with cold surfaces, probably starts to occur when the air temperature is approximately 0°C, and the freezing point for human tissue is about –0.6°C.[59–61]

A reason for confusion is that frostbite might not occur until the skin surface temperature drops well below –1°C. This phenomena was first reported as supercooling at approximately –10°C by Wilson and Goldman.[62] Danielsson[59,60] subsequently explained that their values were 3°C to 4°C too low because of an instrument error. Danielsson has estimated that the skin surface temperature when frostbite first occurs would be between –4.6°C and –8°C.

Even though WCT overcomes some of the problems of Siple and Passel's[11] original work, some of the inherent limitations of indices remain because selection of the standard conditions for any index requires compromise. For example, the activity level is walking at 1.34

m • s^{-1}, so the "calm" condition still involves a forced convection equivalent to a 1.34 m • s^{-1} wind. There is no adjustment for higher or lower activity levels. Although WCT is based on human data, the resistance or insulation of the facial skin layer varies.[51,52,55] Selected skin resistance is most representative of middle-aged or older individuals. WCT has been presented in terms of the time to facial frostbite, but subsequent work by Tikuisis and Osczevski[56,57] has raised questions regarding the efficacy of those predictions. In addition, WCT has no established relationship to the potential hazard for hypothermia. An effort was made to adjust for solar radiation by adding a few degrees to WCT, but the basis for this adjustment is limited.[60]

Required Clothing Insulation

The presentation of WCI/WCT has become focused on the prevention of frostbite rather than hypothermia. In its original form, WCI is a climatic index.[38] Like ET and WBGT, no adjustment is made for clothing or physiological factors. Burton and Edholm[63] brought clothing and metabolism into their calculation of the insulation required to maintain a safe core body temperature.

Holmér[64] calculated the required insulation using equations from Burton and Edholm,[63] Umbach,[65] and Holmér's[66] own equations for required clothing insulation. Holmér concluded that the results for predicting required insulation were essentially equivalent, except that his equations allowed an adjustment for changes in $\bar{T}_{sk}$ and sweating rates.

Burton and Edholm[63] recognized that adjustments were required for wind speed and radiation by proposing the calculation of still air-shade temperature and equivalent shade temperature.[23] Holmér[67] incorporated adjustments for different wind speeds, radiant load, humidity, and the effect of wind and motion on clothing insulation into his required clothing insulation index (IREQ). The IREQ index is presented in ISO-TR 11079.[68] Two levels of insulation can be calculated.

$IREQ_{min}$ is based on a sustainable nonhypothermic state with a $\bar{T}_{sk}$ of 30°C, whereas $IREQ_{neutral}$ refers to maintaining thermoneutrality under specified conditions. For IREQ, neutral condition is actually a state of comfort, whereas the minimal condition is probably at the lower limit of an unimpaired functional state. It is a guideline based on average individuals, assumes an even distribution of insulation, and does not address the problems of local cooling.[23,69]

US ARMY RESEARCH INSTITUTE OF ENVIRONMENTAL MEDICINE MODELS FOR PREDICTING CONSEQUENCES OF EXPOSURE TO ENVIRONMENTAL STRESSORS

Various types of physiological stress-strain models have been developed that have proven useful for generating prevention guidance, assessing environmental health hazards, and predicting environmental stress casualty rates and performance decrements for work-related tasks. Of the suite of environmental models developed at USARIEM, model-based applications have been developed for evaluating the physiological strain associated with exposure to heat stress, cold stress, and altitude-related hypoxia. Modeling in these areas, however, has not proceeded at an equal pace.[70] Heat strain models are currently the most mature and extensively validated. Considerable additional effort will need to be expended to produce equally valid, operationally capable models for other environmental stressors. Eventually, it might be possible to integrate separate models for evaluating different types of environmental stressors into unified applications.[71,72] This would facilitate evaluation of a spectrum of environmental threats to health and mission effectiveness when planning operations that span seasons and environmentally disparate terrain. Likewise, mathematical modeling applications can be embellished to include links to medical handbooks or to evaluate environmental health hazards.[73] Another potential placement for thermal models is on a portable device such as the PDA-based Battlefield Medical Information System–Tactical, which features electronic medical record keeping; electronic medical references, such as the *Special Operations Forces Medical Handbook*; and a telemedicine linkage.[74]

USARIEM Heat Strain Models

The history of the development of heat strain models at USARIEM includes multiple models with differing origins. The first USARIEM thermal model—the USARIEM heat strain model—is labeled the HSDA to differentiate this first, exclusively USARIEM model from the later USARIEM models of heat strain that include elements originating from other sources. The basic structure of the heat strain hybrid model was empirically derived over the course of approximately 30 years, starting in the early 1970s, using data from numerous laboratory and field heat stress studies.[12,75,76] One strength of the HSDA model, and the USARIEM modeling program, is the strong empirical element derived from the physiological studies conducted at the laboratory. The model has been continuously refined and updated. The major strength of this algorithm has been its careful, methodical development and extensive validation.[77] It is a well-accepted model used for many purposes.[78,79] It requires user input for initial environmental conditions (eg, temperature, humidity, wind speed, and radiation), personnel characteristics (eg, height, weight, heat acclimatization status, initial dehydration, and initial core temperature), type of uniform, and metabolic rate or type of activity.[80] Outputs from the model can include the following: maximum recommended work–rest cycle times, maximum single-shot work time, water intake per hour, and core temperature and heart rate as functions of time. Limitations of this model include the validation envelope for core temperature and sweating rates, which, although broad, does not yet include every possible heat stress scenario; heart rate prediction, which has not been as well validated as core temperature and is therefore not used in decision aid applications; predicted heat stress casualty rates, which have not been well validated; and estimates of prediction errors, which are limited and not provided for any of the outputs.

The generic USARIEM heat strain model has been implemented using various computer programming languages and incorporated into progressively more capable and robust decision aids. For example, a prototype, customized, handheld calculator was developed in the mid-1980s that had an executable version of the model embedded in a read-only memory microchip.[13] User estimates of environmental conditions and work rates were entered via the calculator's keyboard. Some inputs, such as type of uniform and activity, required selection of the desired item from a scrolling list. After all necessary inputs were entered, the calculator displayed work–rest cycle and hourly water intake recommendations. It was intended that the heat stress calculator be used by small unit leaders as a heat stress management tool. However, its development did not progress beyond concept demonstration and a prototype. Software for the pocket calculator was adapted for use on personal computers by contractors.[9] This version of the USARIEM heat model, including menus for uniforms and activities, became the basis for the various versions of the HSDA. At present, the process has gone full circle; and, in cooperation with the Army Research Laboratory–White Sands Missile Range, a simplified version of the HSDA has been developed for use with PDAs or similar handheld electronic devices, initially named the mobile heat stress monitor (MoHSM) (Exhibit 2-1).

An obvious drawback of the USARIEM heat stress calculator was that it was not equipped with environmental sensors. A follow-on portable, digital heat stress monitor prototype, however, did incorporate miniature sensors. The HSDA model was embedded in the heat stress monitor. Using the sensor readings, the model generated accurate, location-specific, recommended work–rest cycle times and hourly water intake.[25,81] The sensors included a miniature black globe thermometer and a dry bulb thermometer, but substituted a humidity sensor for the natural wet bulb thermometer. The sensors permitted calculation of the WBGT using an iterative equation to calculate natural wet bulb temperature. This information is displayed on a small screen on the face of the device. The sensors can be stowed to form a compact, hardened package. Despite limited use by US Marine Corps biohazard and chemical clean-up teams and other units, the heat stress monitor did not become a general issue field item. It is currently manufactured in Australia, but only some elements of HSDA are available in the output of the current version. Some of the benefits of the heat stress monitor are available in the MoHSM format installed on a PDA. The concept of incorporating an HSDA model into a device that directly measures weather inputs continues to be pursued in various configurations, including handheld weather instruments.

An example of an effort to implement the USARIEM HSDA and other thermal models has been to incorporate thermal models into integrated meteorological software/hardware systems for acquiring, analyzing, and extrapolating meteorological data in real time. This approach was initially demonstrated as the prototype MERCURY/OMEGA[82,83] system. MERCURY, which produced digital terrain overlay images from gridded weather data, was originally developed by the Army Research Laboratory–White Sands Missile Range in New Mexico. However, the US Army Medical Research and Materiel Command (MRMC) at Fort Detrick, Maryland, assumed oversight for the further development of MERCURY. Under MRMC, MERCURY, which evolved into OMEGA, merged the gridded weather overlay with output from HSDA. It was successfully demonstrated during a pilot project (Figure 2-5) at Eglin Air Force Base. However, MERCURY/OMEGA is a stand-alone product and was therefore difficult to support. Capabilities similar to MERCURY/OMEGA were incorporated into the Integrated Meteorological System (IMETS), which is now a component of the Distributed Common Ground System–Army (DCGS-A).[84]

DCGS-A allows mobile combat planning staff to continuously evaluate and predict the effects of terrain and weather on sensor systems, weapons, and mission. It also uses three-dimensional digital terrain and meteorological databases with near real-time weather data from satellites and scattered ground sensors. DCGS-A software provides a variety of weather products (including models for meteorological forecasting), and the prediction of weapons and sensor system performance as a function of environmental conditions. A number of these weather-related decision aids are incorporated into a virtual toolbox—the Integrated Weather Effects Decision Aid (IWEDA).[84] DCGS-A can generate contour overlays depicting isopleths or contours for temperature, humidity, wind, visibility, and other meteorological properties.

HSDA has been incorporated into DCGS-A and IWEDA. Map overlays depicting the risk of heat injury can be generated by IWEDA. DCGS-A—using user-selected values for uniform ensemble, acclimatization, and work rate—will estimate maximum work time, recommended work–rest cycles, and hourly water requirements. Thus, many of the OMEGA capabilities are provided as part of DCGS-A and IWEDA. Figure 2-6 shows a gridded color-coded HSDA output from IWEDA. Access to IWEDA is available only at higher echelons, but a more accessible version for personal computers (PCs) or laptops—My Weather Impacts Decision Aid (MyWIDA)—is being developed that utilizes weather data from DCGS-A or other weather resources.[85] Additional models for both terrestrial cold exposure and water immersion may be added to the decision aid toolbox. These cold models are based on another USARIEM model, the Six-Cylinder Thermoregulatory Model (SCTM),[86] which is described in Attachment B.

USARIEM also developed a six-node analytic heat strain model called SCENARIO.[87,88] This model has a similar function to that of the empirical model described previously, except that the module that simulates the thermal dynamics of the body is a system of ordinary differential equations derived from basic principles of heat exchange. This model can generate temperature profiles for each body compartment, sweating rate, heart rate, and changes in cardiac output. The model was named SCENARIO to indicate the capability to input a file or stream of inputs, thus recreating an operational "scenario." There is some potential for confusion when SCENARIO is used to evaluate operational scenarios, and as SCENARIO evolves, it will be renamed to avoid this confusion. Core temperature, sweating rate, and heart rate predictions generated by this model have been extensively validated. The ability to predict accurately other compartment temperature profiles or changes in cardiac output, however, has not yet been extensively validated. This model currently predicts heat stress casualty rates using the same mechanism as the empirical model.

A novel derivative of SCENARIO and work by Gagge et al[89] and Moran et al[90] is the initial capability decision aid (ICDA).[91,92] As described in Exhibit 2-2, ICDA uses noninvasive surface measurements collected with the Warfighter Physiological Status Monitor to predict core temperature, mean skin temperature, and sweat rate in near real time. This provides unit leadership with a snapshot of the thermal status of each individual soldier as a physiological strain index based on core temperature and heart rate,[90,93] and provides a basis for projecting water requirements and the potential for near-term heat injury with continued heat exposure.

Cold Strain Models

Operations and training in cold areas expose individuals to risks of cold weather injuries and hypothermia. Very cold weather can dramatically reduce individual and unit operational capabilities. Preventing cold injuries keeps experienced soldiers on the line so that missions can be completed as efficiently and quickly as possible with minimum casualties. Personnel evacuated for cold injuries can be replaced by less experienced personnel who will be at higher risk for becoming combat casualties and for succumbing to cold injuries.

Because most individuals cannot reliably estimate safe durations of cold exposure, model-based decision aids can be useful for quantifying cold stress injury risk and generating exposure limit recommendations to reduce the risk of cold injuries to as low a level as possible. A specific use for cold strain models is to generate cold exposure tables based on minimum allowable extremity or core temperatures. Such guidance can then be incorporated into safety and casualty prevention standard operating procedures (SOPs) and doctrine. The WCT is an example of how a simple cold model has been incorporated into military doctrine.[92]

Lumped- and distributed-parameter compartmental models for the entire body and extremities or representative digits have been developed for predicting generalized hypothermia and peripheral cold injuries. Because the transition of physiological responses to heat and cold stress is not linear, a compartmental heat strain model cannot be used directly for also predicting hypothermia. Separate models for heat and cold strain, however, can be linked within a software implementation of a generalized temperature response model so that the appropriate set of coefficients and parameters are used for the desired range of environmental conditions. If only one compartment model is used to span the physiological responses to both heat and cold, the single set of coefficients must be calculated using appropriate data from both heat and cold exposure studies. This would also require that validation spans both cold and hot conditions, whereas using separate, previously

EXHIBIT 2-1

MOBILE HEAT STRESS MONITOR GUIDE*,†

The US Army Research Institute of Environmental Medicine has spent years developing and improving models to predict human thermal responses. Through an ongoing Memorandum of Agreement with the US Army Research Laboratory, one of these decision tools is deployed for use on handheld Personal Digital Assistants (PDAs). It is still considered developmental and is not available for purchase. The latest modifications of the biophysical algorithms are used (heat strain decision aid [HSDA] 2004C model), and current system specifications follow, although the model can be installed on various platforms. The PDA with the HSDA model installed was initially named the mobile heat stress monitor (Exhibit Figures E1-1 and E1-2).

Other applications of HSDA use real-time weather information via network connection. This version of the model requires user input of weather, work rate, and clothing prior to calculations. Unlike the PC version that requires numerical inputs for weather parameters, work rate, and clothing heat transfer properties, the mobile handheld version uses more limited data input. Default standard values are used in calculations instead of soldier-specific data, such as height, weight, acclimation, and dehydration status. These simplifications allow the user to make general predictions for a group of soldiers with minimal data entry. Finally, many standard outputs of the PC version of HSDA are suppressed in the PDA version for simplicity and visual clarity.

PDA Inputs
- Geolocation (latitude and longitude; current default is Natick, Mass)
- Month, day, and time of day
- Temperature (°C or °F)
- Weather: clear *or* partly cloudy *or* cloudy *or* precipitation
- Wind: calm *or* light *or* moderate *or* strong
- Humidity: dry *or* normal *or* moist
- Work rate: resting *or* very light *or* light *or* moderate *or* heavy
- Clothing: BDU (battle dress uniform) *or* MOPP-1/-2 *or* MOPP-3/-4 (with other uniform configurations to be added). The term "Mission-Oriented Protective Posture" (MOPP) refers to the level of chemical protective clothing worn.

PDA Outputs
- Probability of heat stress injury (%)
- Optimum work–rest cycle time (≤60 minutes/hour)
- Maximum endurance time (up to 300 minutes)
- Water Requirements (canteens/hour, 1 canteen = 0.9 liters)
- WBGT (°F)

How to Use the PDA
- Turn on PDA power by pressing the on/off button.
- Next, use the stylus to tap "Start" at the top left of the screen display to show menu choices.

Fig. E1-1. The PDA used for the mobile heat stress monitor is the Microsoft Pocket PC (Microsoft Corporation, Redmond, Washington). Model ID: Hewlett-Packard iPAQ h545 (Hewlett-Packard Company, Palo Alto, Calif) with the HSDA2004C model installed using the PDA version of decision support tool files. HSDA: heat strain decision aid; PDA: personal digital assistant.

(**Exhibit 2-1** *continues*)

Exhibit 2-1 *continued*

- Tap "LocalHeatStress" or its icon shortcut to launch the decision support tool. To change numeric inputs, first use stylus to highlight item to be changed.
- Then, use stylus taps on keyboard to change inputs as desired.
- Tap stylus on list boxes to choose from options. All environmental inputs, except air temperature, are selected from short menus of conditions. For example, the choices for humidity are dry, normal, or humid, which correspond to 20%, 50%, and 80% relative humidity, respectively.
- The solar load is computed using the location in latitude/longitude, date, local time, and the menu input for sky condition. If the PDA has a Global Positioning System capability, the location can be accessed automatically, and the fault date/time can be automatically retrieved from the system.
- To obtain the output information, tap the COMPUTE button for calculations and EXIT button to stop simulations.

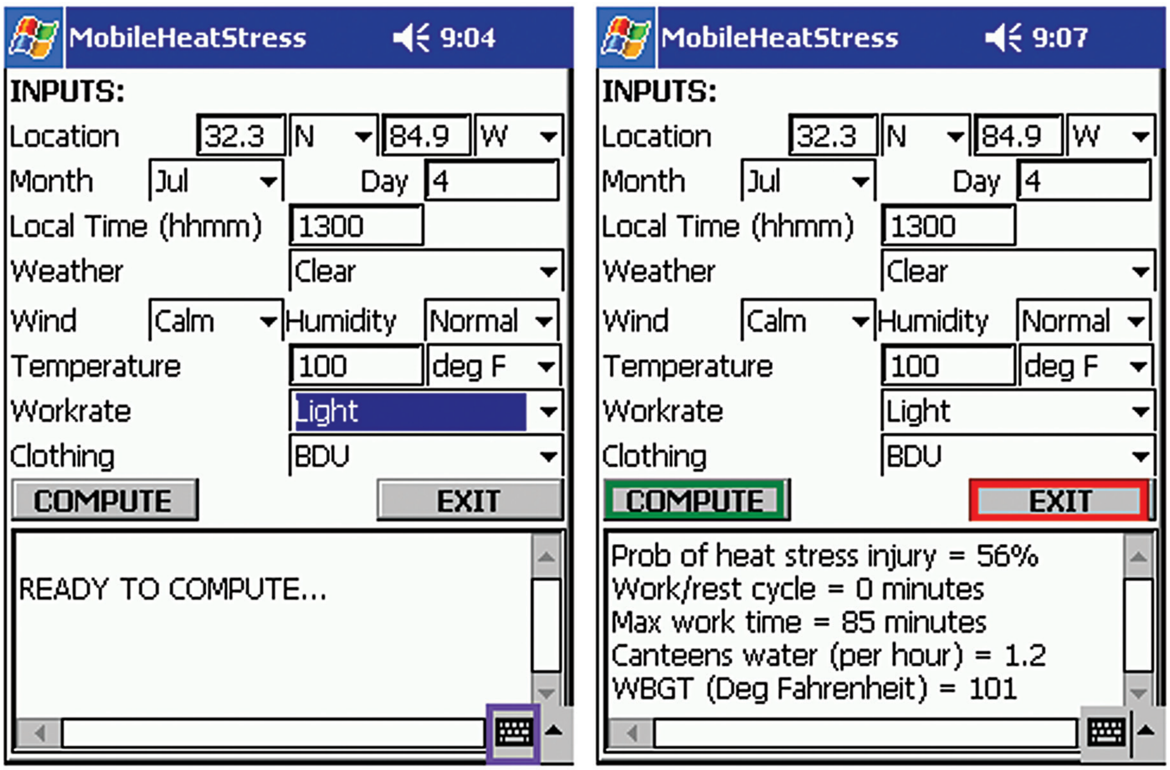

Fig. E1-2. Mobile heat stress monitor input and predicted heat strain at Fort Benning, Georgia, on July 4. (**Left**) Selected inputs, including a high air temperature (100°F), moderate humidity, full sunlight, the battle dress uniform (BDU), and a light work rate. (**Right**) Outputs indicate a relatively high probability of heat injury if the maximum work time of 85 is exceeded or hydration is not maintained, and no work–rest cycles are sustainable for this exposure and activity level. Max: maximum; Prob: probability; WBGT: wet-bulb globe temperature.
Photograph: Courtesy of the US Army Research Laboratory, White Sands Missile Range, New Mexico.

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validated models would require verifying the transition points at which the algorithm switched from one model to the other and did not cause factitious transients.

As indicated previously, cold model development has proceeded in two directions. Most cold models can be categorized as either whole-body or extremity/digital models. Whole-body models usually address hypothermia, whereas frostbite or loss of function tends to be the more immediate concern for the extremities. This reflects the circulatory response to cold

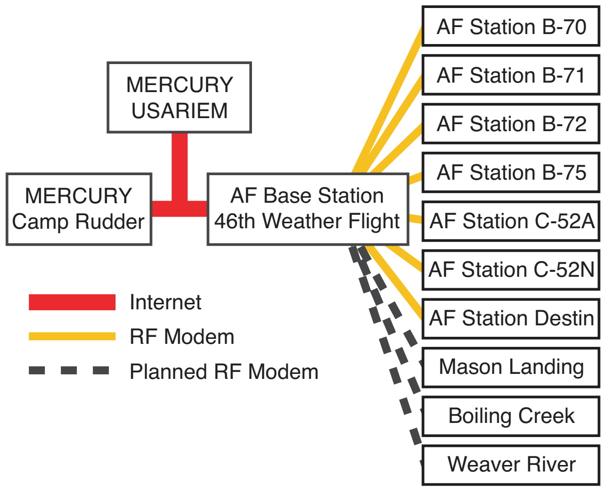

Fig. 2-5. Schematic diagram of the MERCURY/Ranger Test Bed at Eglin Air Force Base in Florida. AF: Air Force; RF: radiofrequency; USARIEM: US Army Research Institute of Environmental Medicine.

exposure, which essentially sacrifices the extremities by vasoconstriction to preserve the core body temperature and function.

Frostbite of the fingers, toes, and face tends to be the primary risk for active soldiers. In addition to the initial pain and loss of digital function, the appearance of frostbite, with the discoloration and the fear of or actual occurrence of gangrene and amputation, can have a psychological effect disproportionate to the immediate danger. The loss of manpower, strain on medical facilities, and long-term disability caused by frostbite are, however, very real. In addition to the WCIs, other models have been developed to predict probability of frostbite for a given set of exposure conditions.

Cold digit compartment models require that users input digit dimensions, blood flow, initial compartment tissue temperatures, the biophysical properties of gloves or boots, plus air and ground temperatures. The typical operational output of interest is the time for the tip of the digit to reach a threshold temperature (eg, 5°C or 41°F), below which there is increased risk of peripheral cold injury.

Some peripheral hypothermia models mathematically incorporate the effects of cold-induced vasodilation (CIVD).[93] This phenomenon effectively balances competing requirements for heat-conserving vasoconstriction and nutritive vasodilation. Unfortunately, readily identifiable individual factors that can predict CIVD have not been adequately established to include this in these models. Furthermore, without being able to reliably predict which personnel will respond to declining digit temperatures with CIVD, the longer exposure times predicted with a CIVD model would put those without CIVD at risk for peripheral cold injuries.

A numerical model of a generic distal extremity (eg, finger) exhibiting simulated countercurrent arteriovenous heat exchange for predicting temperature response of digits to cold stress has also been developed by Shitzer and colleagues[94] at USARIEM. The model (Attachment A) is based on the geometry of a multilayered cylinder and sophisticated control theory. At the time of its development, the computational requirements for a complex, multinode model exceeded the computational resources that would be available in an operational setting. Obtaining the requisite, detailed data to expand the validation of the model has also been difficult. The focus at USARIEM is to link a simpler extremity model to the whole-body model.

A limitation of WCT and other windchill models presently incorporated into military doctrine[92] is that these models predict only local frostbite of the extremities and/or comfort. Although frostbite tends to be the primary risk for well-dressed soldiers who engage in activities that result in significant levels of metabolic heat production, when soldiers are forced into a sedentary state or exposed to extreme cold without adequate clothing, hypothermia is a significant risk. Present windchill models do not address hypothermia. In addition, partial immersion is a confounding condition.

Tikuisis and colleagues,[95] working at USARIEM and DRDC Toronto, developed several versions of whole-body cold models for both dry and immersed individuals. Through access to the cumulative USARIEM database, Tikuisis et al were able to quantitatively identify the importance of body fat during immersion. More recently, Xu and colleagues[86] developed an improved model, the SCTM, that incorporated both heat and cold effects for both terrestrial and immersion states. Additional applications using SCTM are discussed in Attachment B.

Models of the more extreme immersion state are easier to validate because of both greater availability of data and the less complex biophysics of immersion in a liquid when, in the nude state, virtually the entire body surface is exposed to the same convective stress. Whole-body cold models become more complex with clothing, partial immersion, wet clothing, or the greater complexity of conductance through foot and hand contact, convection to air at varying velocities, evaporation, and radiant exchange in different directions. Because terrestrial cooling is sensitive to variations in clothing, wind speed, and activity over a wide range of air temperatures above and below freezing, it is particularly difficult to develop an adequate database for model development.

Moran and colleagues[96] proposed a cold strain index (CSI). They improved the version of CSI[97] for dry or terrestrial cold exposure, suggesting that cold strain is a product of both core and extremity surface cooling. It is unlikely that an individual with severely frostbitten hands will be able to function as a soldier during operations, nor survive for an extended period of time without assistance. A successful cold model must therefore account for both extremity and whole-body cooling. Thus, recent efforts at USARIEM, such as SCTM, have attempted to link whole-body and extremity cooling.

High-Altitude Models

There is currently no operationally useful, validated model for accurately predicting soldier responses to acute, subacute, or chronic exposure to the hypobaric hypoxia of high altitudes.[70] One fairly comprehensive physiological response model exists, but it does not link predicted physiological responses with altitude illness rates and has not been validated for use in military operational settings.[98] Adding to the complexity of developing a comprehensive casualty prediction altitude exposure model is that ascent to high mountain altitudes is typically associated with simultaneous exposure to cold, harsh, and labile weather, causing significant risk for hypothermia and peripheral cold injuries, increased intensity of direct and reflected ultraviolet radiation (which predisposes one to skin and ocular injuries), and exposure to rugged terrain (which predisposes one to traumatic injuries). Also, an operationally useful high-altitude casualty prediction model should include the effects of prophylactic medications that have been found effective in reducing the risk and severity of high-altitude illnesses. A comprehensive high-altitude exposure model ideally would integrate these disparate but related factors to accurately predict the physiological strain, injury, and illness rates for proposed high-altitude missions or, conversely, generate recommended ascent profiles to limit altitude illness rates below a specified maximum level.

Independent or predictor variables for constructing high-altitude physiological and medical outcome models would necessarily include environmental, mission, and personal factors. Mission-related factors would be extremely important for predicting physiological strain and medical consequences of ascent to high altitude. Absolute altitudes and proposed rates of ascent determined by command-imposed time lines for reaching mission objectives would be major environmental and mission determinants of altitude illness rates.

Estimated compliance rates with prescribed prophylactic medication regimens against altitude illness before and during ascent would be another important factor. Predicted environmental temperatures and biophysical properties of uniforms; solar intensity; number of hours of day versus night operations; percentage of personnel who will not have or will lose their sunglasses; estimates of amounts of potable water available per person per day; and an index of terrain ruggedness could all qualify as predictor variables for altitude, solar, cold, and traumatic injuries and illnesses that would be of operational importance for missions in high mountain areas. A comprehensive predictive altitude model, therefore, could be useful to commanders and their staff, and for advising medical officers to develop reasonably accurate quantitative estimates of the injury and illness rates associated with alternative approaches to achieving combat, peacekeeping, civil action, or disaster relief objectives in high mountain areas.

Without a trusted prediction model to quantify these types of potentially preventable health risks, operational and tactical planning staff might not adequately consider the relative importance of these problems when selecting among alternative mission strategies. Medical planners could also use a comprehensive predictive altitude model to develop balanced medical support requirement plans. This would include better specification of evacuation and treatment resources. For example, evacuating ill or injured personnel in high, rugged, stormy, mountainous environments will often be resource intensive.

Assumptions and Biomedical Models

Assumptions are an inescapable aspect of model development (including notional models). It is recommended, though, that they be explicitly identified, categorized, and their existence and information disseminated to users of related models. Users of model-based analysis and decision tools should understand a model's operationally important explicit and inherent assumptions and determine to what extent they might affect the accuracy and validity of its predictions for specific applications. For example, the USARIEM heat strain model has been used to develop recommended work–rest cycles and water intake tables for various deployment handbooks.[27] Such tables are accompanied by a list of the important assumptions that the user must check before utilizing the tables. The assumptions include the following: that the troops for which the recommendations will be applied are basically healthy and adequately nourished (because the data used to develop the model were obtained from healthy nourished soldier volunteers), and that everyone starts out adequately hydrated (because the tables were created using an initial condition of no

EXHIBIT 2-2

INITIAL CAPABILITY DECISION AID THERMAL PREDICTION MODEL[*,†]

The initial capability decision aid (ICDA) model is a heat stress prediction model developed for monitoring the physiological status of soldiers. It is a basic and abridged model derived from elements of the US Army Research Institute of Environmental Medicine (USARIEM) human thermal physiological simulation computer model, SCENARIO,[1] and the Gagge model.[2] The model can be loaded with anthropological characteristics of an individual (ie, height, weight, and clothing), group means, or default population values. Real-time inputs of measured heat rate and local weather (eg, temperatures, wind, relative humidity, and estimates of radiant load) are used by the computer model to make real-time predictions and estimates of the subjects' physiological status or other physiological parameters.

A main purpose for constructing this model was to predict time estimates of the internal body temperature (T_{cr}), sweat rates (SR), and hydration status of soldiers in a battlefield situation. For instance, T_{cr} is the traditional and common physiological parameter for heat strain assessment, as it reliably indicates impeding injury.[3,4] However, measuring T_{cr} is invasive and can be impractical for real-time monitoring of soldiers dispersed over a large area and exposed to heat stress while engaged in long hours of varied and unpredictable tasks. Although obtaining "true" values of many parameters from environmental, physiological, and operational conditions is desirable and increases the model's accuracy to assess soldiers' status, alternatives for the worst-case scenario (eg, losing signals from sensor devices, wrong calibration, or conflicts between sensors) still need to be considered. For these reasons, ICDA was developed to predict physiological responses to battlefield situations from a minimum number of noninvasive inputs.

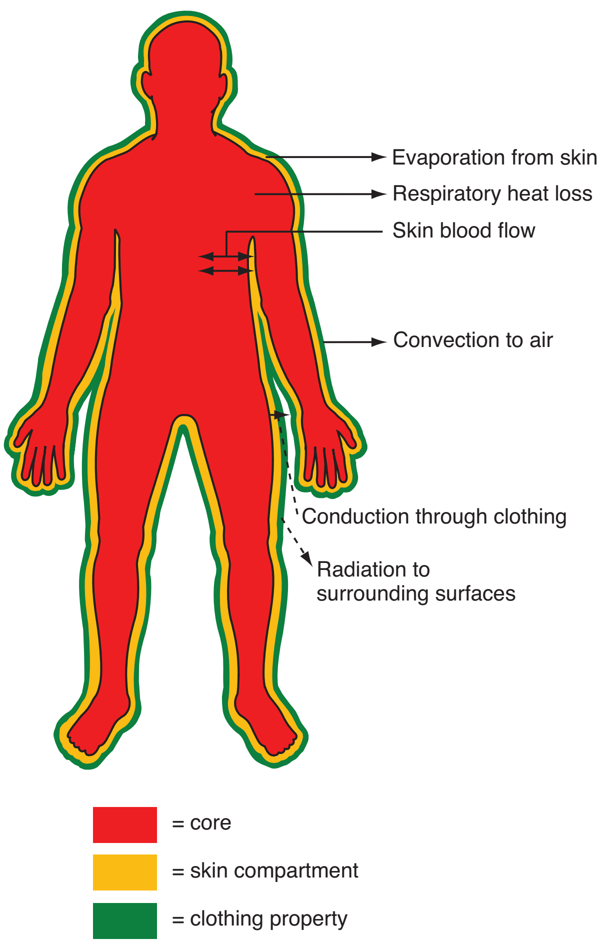

Fig. E2-1. Schematic of core, skin, and clothing compartments.

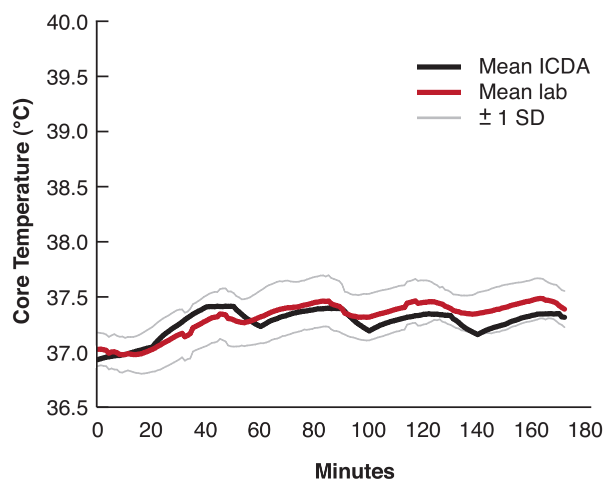

Fig. E2-2. Summary comparisons between mean measured and predicted core temperatures from different heat studies. Heat study 1 (27°C, 75%; hot weather Battle Dress Uniform; n = 9).
ICDA: initial capability decision aid
Illustration: Adapted with permission from Santee WR, Berglund LG, Cardello A, Winterhalter CA, Endrusick TL. *Physiological Assessment of Volunteers Wearing Battle Dress Uniforms (BDUs) During Intermittent Exercise.* Natick, Mass: US Army Research Institute of Environmental Medicine; 2006. Technical Report T06-06, unpublished data, June 2006.

(**Exhibit 2-2** *continues*)

Exhibit 2-2 *continued*

The thermal physiology of the ICDA model is represented schematically in Exhibit Figure E2-1, where the human is modeled as two physiological compartments (core and skin) surrounded by a passive clothing compartment. Within a compartment, the properties are uniform (ie, everywhere within the core at time t, T_{cr} has the same value). All metabolic heat production (M) occurs in the core. Some heat is lost directly from the core to the environment by respiration; all of the other heat from the core is transferred to the skin by conduction or convection with skin blood flow. The primary method used to regulate T_{cr} is achieved by controlling blood flow. Exhibit Figures E2-2 and E2-3 present the results for T_{cr} predictions from two of three heat studies used to validate the model. More complete information, including data from all three studies, are presented in other reports and publications.[5] Recent reports from wars in Iraq and Afghanistan indicate that faster access to medical/surgical care and identifying evacuation situations would save more soldiers' lives.[6,7] The current strategy to shorten the time lag between injury and treatment is to position a small surgical care unit near the battlefield.[7] The model can contribute this effort by forecasting both real-time and future probabilities of soldiers' health status by notifying unit medical personnel and command elements on the battlefields. The ICDA will also provide a longitudinal projection of SR, which can be used to predict soldiers' dehydration status and water requirements. Thus, logistics personnel can plan for water delivery to meet the projected demand and the associated cost, and soldiers can sustain their physical and cognitive performances by preventing dehydration.

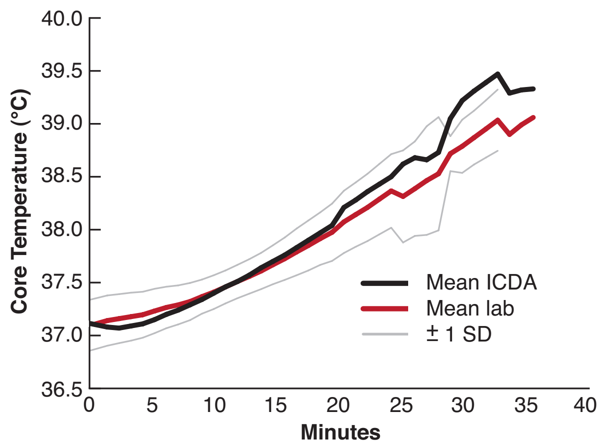

Fig. E2-3. Summary comparisons between mean measured and predicted core temperatures from different heat studies. Heat study 3 (35°C, 45%; protective garment; $n \leq 8$).
ICDA: initial capability decision aid
Illustration: Adapted with permission from Latzka WA, Sawka MN, Montain SJ, et al. Hyperhydration: tolerance and cardiovascular effects during uncompensable exercise-heat stress. *J Appl Physiol*. 1998;84:1858–1864.

Predictions of soldiers' thermal status during heat stress are promising, particularly for T_{cr}, using this simplified model. To improve predictions of skin temperature ($\overline{T}_{sk}$), the existing databases should be evaluated to determine which $\overline{T}_{sk}$ measurement site best represents the combined impact of individual variability, clothing, environment, and operations on $\overline{T}_{sk}$, and is, therefore, the best site to use for model development and validation of $\overline{T}_{sk}$ predictions. Similarly, for SR predictions, the trends of individual SR patterns need to be carefully evaluated to further refine this model. Lastly, it is recommended that ICDA be applied to real-time situations in both laboratory and field training exercises for future T_{cr} sensitivity analysis and further model development.

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Data sources: (1) Kraning KK, Gonzalez RR. A mechanistic computer simulation of human work in heat that accounts for physical and physiological effects of clothing, aerobic fitness, and progressive dehydration. *J Therm Biol*. 1997;22:331–342. (2) Gagge AP, Fobelets AP, Berglund LG. A standard predictive index of human response to the thermal environment. *ASHRAE Trans*. 1986;92:709–731. (3) Amos D, Hansen R, Lau WM, Michalski JT. Physiological and cognitive performance of soldiers conducting routine patrol and reconnaissance operations in the tropics. *Mil Med*. 2000;165:961–966. (4) Pandolf KB, Goldman RF. Convergence of skin and rectal temperatures as a criterion for heat tolerance. *Aviat Space Environ Med*. 1978;49:1095–1101. (5) Yokota M, Berglund LG. *Initial Capability Decision Aid (ICDA) Thermal Prediction Model and Its Validation*. Natick, Mass: US Army Research Institute of Environmental Medicine; 2006. Technical Report T06-9. (6) Bilski TR, Baker BC, Grove JR, Hinks RP. Battlefield casualties treated at Camp Rhino, Afghanistan: lessons learned. *J Trauma*. 2003;54;814–822. (7) Gawande A. Casualties of war—military care for the wounded from Iraq and Afghanistan. *N Engl J Med*. 2004;351:2471–2475.

more than 1% dehydration). Other assumptions are that it would be impractical to create separate tables for every possible combination of the situationally less important independent variables. Therefore, representative values are used. The extent to which actual conditions deviate from these assumptions, as well as how the recommended or assumed values should be adjusted, needs to be assessed by the users if direct consultation with the modeling group that created the tables is not feasible.

Numerous legitimate assumptions are frequently invoked during model derivation and development.

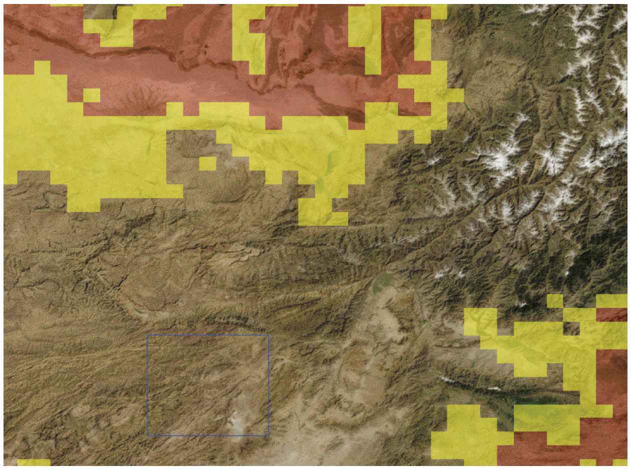

Fig. 2-6. Graphic representation of the risk of heat injury generated by the Integrated Weather Effects Decision Aid (IWEDA). Color-coded output for the risk of heat injury, based on the USARIEM Heat Strain Decision Aid (HSDA), which is incorporated into the IWEDA component of the Distributed Common Ground System–Army (DCGS-A) weather "toolbox." The map represents, for each colored pixel, the highest risk of thermal injury projected for an area in Afghanistan for a 24-hour period (0700 on May 10, 2011 to 0800 on May 11, 2011) for warfighters wearing the Army Combat Uniform with body armor while engaged in moderate activity, and assumes partial (5 days) heat acclimatization. Red represents a greater than 50% risk of heat injury, amber indicates a risk between 25% and 50%, and no color (usually represented as green) indicates the risk is below 25%. The color coding may be adjusted to reflect different risk levels. For the whole area, each colored pixel represents a 15-km area, and the temporal resolution is 3 hours. For the smaller area outlined in blue, a more detailed weather forecast, a Weather Running Estimate (WRE)—based on interpolation, surface observations, and upper air soundings—is available. For the WRE, the resolution is 1.5-km pixels for 30-min intervals. Information for this area, with an associated projection of risk from IWEDA, is presented in a colored chart that presents the threat level for an expanded 48-hour timeline. Additional information regarding maximum work times, work–rest cycles, and water requirements is available from DCGS-A.
Photograph: Courtesy of US Army Project Manager, Distributed Common Ground Station–Army.

They might be necessary to simplify complex processes, to make the modeling effort tractable, or to permit spanning knowledge gaps that would otherwise prevent model completion. Assumptions might be necessary when users want a practical, easy-to-use model in lieu of a cumbersome, full-featured, high-resolution version. Assumptions can also be necessary to account for the effects of uncertainty and the seemingly random variations. In addition, they might be necessary during, or an inevitable consequence of, the model implementation process. For example, the form of derived or empirically selected equations, the numerical methods used to generate output, and the inherent logic in a software realization can affect the accuracy and stability of the model. Furthermore, although the many equations in a complex model might be stable and well-behaved when evaluated individually, often there remains the unproven assumption that the overall model will also be stable and well-behaved within the variable space over which each equation individually was determined to be valid.

Most users of model-based products will not have the technical background, interest, or time to verify model correctness or validation. Therefore, they must usually assume that the model was developed properly, that algorithms are correct, that the forms of the associated regression equations are appropriate, that the implementation is debugged, and that the model and implementation have been validated. As referenced in chapter 1, there is a formal process for validation, verification, and accreditation (VV&A) of models. Model developers must systematically establish the credibility of their products. This can be accomplished by organizing a model development process with documented control mechanisms that will ensure (to the greatest extent feasible) and certify model correctness and validation prior to product release. Incomplete, operationally invalidated models, however, are useful for proof-of-concept demonstrations and to elicit feedback from prospective users during the concept development and exploratory development phases of a modeling project.[73]

Physiological heat strain models, for example, are often associated with a number of important assumptions. Algorithms that generate predictive core temperature profiles versus time do not explicitly model the effects of skin temperature. However, skin temperature is clearly a relevant factor in thermoregulation. It determines the core-to-skin and skin-to-ambient temperature gradients that influence rates of conductive heat flow from core to skin and skin to environment. Also, the vapor pressure and rate of evaporation of the layer of sweat adhering to the skin's surface are functions of skin temperature.

A certain amount of inaccuracy in some types of predictive heat strain algorithms might be related to not explicitly including terms for skin temperature. However, skin temperature effects will be implicitly included in heat strain models whose coefficients were obtained using data from heat stress studies. The experimental data in such situations implicitly reflect all the thermoregulatory processes affecting changes in core temperature. For example, actual core temperature measurements include the effects of skin temperature, sweating, and changes in skin blood flow. Therefore, an empirical regression model can predict core temperature quite reliably, even though skin temperatures are not explicitly delineated in the model. In such circumstances, the effects of skin temperature are in the model, but distributed among its coefficients in a manner that is not separable or directly discernable. These types of predictive thermal strain models will be algorithmically less complex than if skin temperature effects were explicitly included. Initial skin temperatures during use of such a model are necessarily assumed to be those from the data from which the model was developed. If skin temperature is modeled explicitly, users may then have a mechanism for entering situation-specific initial skin temperatures that can result in more accurate core temperature predictions.

A serious mistake of modeling the effects of skin temperature could occur, however, if an analytically derived model with empirically determined coefficients, but not modeling skin temperature, was "enhanced" or upgraded with additional skin temperature equations or terms having coefficients calculated from separate data. This could result in an incorrect model, because skin temperature effects would be duplicated, to some extent, using such an approach. A similar, but incorrect, alternative that is sometimes used in practice is the inclusion of terms to explicitly model a new process variable, such as skin temperature (or any other factor not in the initial model), and then "tweaking" miscellaneous parameters in the new and original terms until the predictions from the enhanced model match experimental data. With this approach, the modeler, in effect, arbitrarily reallocates the unmodeled thermoregulatory effects between new and previously defined coefficients.

The preferred method for expanding a model requires that parameter identification and model validation be completely redone. This can be facilitated by the availability of a robust statististical analysis application for performing complex multiple regressions conveniently linked to large data sets from an extensive database of heat stress study results.[99]

The body tissue compartment is a common abstraction used in the formulation of biomedical and pharmacological models. It involves important simplifying assumptions. In compartment models, portions of the body (eg, the digits in models for predicting maximum cold exposure times) are neatly partitioned into a small number of discrete stereotypical geometric volumes (eg, concentric cylinders) having homogeneous tissue and biophysical properties. A typical compartment structure depicted graphically has a central blood compartment and a solid cylindrical core compartment representing viscera, intrathoracic, and cranial tissues surrounded by successive concentric hollow cylinders representing muscle, fat, vascular skin, and nonvascular skin. Each compartment can also be represented as a single point having the temperature and biophysical properties of all other points in the compartment. This is one reason why a compartment model is also referred to as a lumped-parameter model. Except for the outer skin surface, the surface areas of the intercompartmental interfaces are not actually measurable. They are calculated in accordance with the geometric model using best obtainable estimates of average compartment volumes and densities. This type of model implicitly assumes that properties and values of the predicted variables are time-dependent, but not functions of location along the interface.

Heat and cold strain models for predicting tissue compartment temperature profiles intrinsically assume that all points in a compartment are always at the same temperature and change simultaneously by identical amounts. Therefore, this results in a low-resolution model that admits transcompartmental, but not intracompartmental, temperature gradients. This restriction necessarily implies that heat flows infinitely fast within compartment boundaries. This would be an untenable assumption if it were not for the extensive and fairly uniform plexus of blood vessels that traverse most tissues. This allows rapid convective heat transfer between compartments, thereby creating the tendency for temperature equalization within tissue compartments. The compartment assumption is, in a sense, an abstraction of the details of this convective blood flow process. For most practical applications, this assumption results in a sufficiently accurate and reliable heat or cold strain prediction model.

Greater predictive accuracy and spatial resolution can theoretically be obtained with distributed-parameter models; however, their solutions are often more difficult to derive. This class of mathematical model also uses compartments, but the biophysical properties of tissue within each compartment are specified with greater resolution as functions of specific location. Likewise, values for predicted variables are functions of exact intracompartmental location and time. Distributed-parameter models determine time-dependent heat conduction from point to point within each compartment. There is not just one temperature per compartment; rather, there are as many separate temperatures as permitted by the spatial resolution of the solution method. As advantageous as that might be, this type of model is not as commonly used as the lower resolution, lumped-parameter type, because it is much more difficult to identify the functions or specific values describing spatially varying tissue properties and initial conditions. Also, a distributed-parameter model is generally more difficult, expensive, and time-consuming to validate, if it can be done at all. This is because validation requires that initial values for the predicted variables be obtained for points throughout the volumes being modeled. For many variables, the technology might not exist to make this possible. Also, even if a distributed-parameter model can be validated in carefully controlled experimental settings, it can be impractical during operational use to fully and accurately determine or specify the functional form of a large number of initial and boundary conditions.

Other modeling assumptions that do not involve simplification of morphological characteristics and the natural distribution of tissues and biophysical property gradients can be illustrated by examining the link in the USARIEM heat strain model between predicted core temperature response and likelihood of heat stress casualties. The more mathematically complex portion of the model is the empirically derived algorithm that predicts core temperature as a function of numerous, situation-specific personnel and environmental factors. The other component predicts heat stress casualty rates as a single function of the calculated core temperature. A 50% rate of heat stress casualties is predicted when core temperature reaches a mean of 39.5°C (103.1°F). The casualty rate function has an effective standard error of approximately 0.3°C (0.54°F), so that a 95% heat stress casualty rate is associated with a core temperature of 40.1°C (104.2°F).

The predicted casualty rate refers to heat stress-related illnesses that require evacuation to a medical treatment facility. Unfortunately, the model, as it currently exists, cannot partition the predicted total heat stress casualty rate into diagnostic categories, such as dehydration, dermatological conditions, heat exhaustion (mild, moderate, recurrent), or heatstroke (moderate, severe, lethal). This limitation restricts the ability of extending the model in ways that would be useful for medical planners. For example, diagnostic resolution is required for estimating the medical resources necessary to transport, treat, and rehabilitate different types of heat stress casualties. The heat strain model would need to be expanded to be able to predict different types of heat illness. It is unlikely that such an extended heat illness prediction module would be accurate if the output were a function of core temperature only. Additional variables—including skin temperature, dehydration, and rate of core temperature increase, as well as direct dependency on mission (eg, work rates) and environmental input factors—would be necessary considerations. To link casualty and required medical logistics support would require adding a third component to the current model.

Development of a component for predicting the logistic requirements for a potentially complex and dynamic mix of the types of heat illness would need to be derived by obtaining data retrospectively from treatment records, or preferably by conducting prospective studies that would collect, in an unbiased and as complete a manner as necessary, representative medical logistical data on heat stress illness. In Chapter 12, an example of a database of medical records—the Total Army Injury and Health Outcomes Database—is described. Logistical support requirements for the evacuation, treatment, and disposition of heat stress casualties could be modeled as a function of available medical evacuation and treatment personnel and technology, type of operational scenario, terrain, tempo, and other complex variables.[71] To develop a predictive logistics component for the overall model, observational or experimental data regarding requirements for evaluation, treatment, and evacuation resources required for each type of environmental stress casualty would need to be obtained.[100]

Validation of Biomedical Models

All models used for training or decision-making should be validated.[101] Although, as noted previously and referenced in Chapter 1, there is a formal process for VV&A (MIL-STD 3022), the application of the process to physiological models presents a challenge. This is a process that verifies that there is no statistically significant difference between measured and predicted outcomes. From a practical standpoint, however, the deployment of model-based products usually cannot await complete validation. The number of inputs for the mathematical algorithms of the models and the alternative branching in the traversal of many logical structures in the software implementations can be so complex and numerous, or span such a wide range of plausible values, that it is not feasible to validate predicted effects of every possible combination of values for the independent variables. Validation of models and simulation algorithms can be performed for only points or small areas or volumes at a time in a hyperdimensional space defined by the plausible range of values for the independent variables. Because the envelope for the validated region can usually be expanded only by a limited amount through any particular validation study, extensive validation of a model can become very costly and extend over many years or even decades. The envelope of the independent variable regions for which a model has been validated expands as successive validation studies are performed.

Statistical evaluation is required during validation because, although models are often deterministic, measured data contain noise or variability for a wide variety of reasons, including the changing influences of variables and factors that are not measured or controlled. Compared with the output from deterministic models, which always generate the same output values for the same initial conditions, real-world data always include noise; that is, model-based predictions will not usually precisely match actual results. Because model-based predictions are not always exactly correct, some individuals categorically reject their use. However, well-constructed and validated models, even if not always precisely correct in their predictions, are often more accurate, consistent, and able to evaluate more factors simultaneously than unaided subjective estimation processes.

The "failure" of models is sometimes the result of inflated expectations. Physiological responses to equivalent stress, even for the same individual, demonstrate a degree of variability. In addition, measurement methodology allows some error. Under field conditions, any claim of a precise replication of conditions should be suspect. Thus, a categorical rejection of a model when it does not exactly match field data is naive. In addition, no event can be completely physiologically isolated. Wallace et al,[102] for example, in an epidemiology study, determined that heat injury was strongly correlated to a history of cumulative exposure to heat stress over at least the previous day. A practical demonstration is that the NWS issues a heat wave warning based on the persistence of high air temperatures over a 3-day period, rather than exposure to high temperature, per se. In a similar manner, as an operation progresses, most individuals are unable to maintain peak physiological conditioning as progressive sleep deprivation, muscle fatigue, nutritional short falls, and mental fatigue take a toll. At present, no model compensates for all aspects of a sustained operation.

Pielke and Conant[103] used weather forecasts to illustrate how a better understanding of models could establish their utility despite some inherent error. As they indicate, weather forecasts are model predictions, and practical experience indicates that those predictions are not wholly accurate. However, most people do not completely reject or dismiss the forecasts due to that inaccuracy. Certainly, no one rejects weather reports based on a one-time over- or underprediction. Rather, we learn to work with the limitations of the predictions and, as we become more familiar with the inherent error, we learn to take the possibility of error into our decision-making process. Familiarity with predictions from a specific model promotes better use of the model. By incorporating models into training doctrine, units will be prepared to use the guidance during actual operations.

Most models are deterministic abstractions of natural processes that exhibit considerable variance when repeatedly measured at each value of the independent variables. Mathematical models can be constructed to incorporate such variation if error terms, obtainable from regression analysis results for the parameters of interest, are incorporated into the model rather than discarded, as is often the case in practice. The parameters or coefficients in modeling equations would then be statistically parameterized with corresponding means and standard deviations (for determining variance of predicted results for individuals) or standard errors (for determining variance of predicted results for a group). Although the estimates of true (often unknowable) model parameter values are usually assumed to be normally distributed, the distribution of the predictions might not be. When simple mathematical algorithms incorporate parameter variances, it might be possible to analytically determine distribution (eg, normal, chi square) of the predicted output. This is usually not possible for a complex mathematical algorithm; Monte Carlo simulation and hypothesis testing methods are required to characterize the statistical distribution of the output.

Differences between predicted variables and measured values will always occur because a model cannot fully account for all the complexities (manifesting as apparent randomness) of personal, environmental, and mission-related processes. Another source of disparity between predicted and actual responses is measurement error for user inputs. Primarily, this refers to the uncertainty or error in ascertaining the true values for the initial conditions. For example, a heat strain model might require the user to input a value for the ambient WBGT, and/or the three weather variables used to compute WBGT. However, WBGT values, as a function of dynamic weather patterns and terrain, often are a relatively rapidly changing set of inputs. For example, WBGT values obtained 5 km, 1 km, 100 m, or 1 m away from a group of working individuals can result in significantly different model-generated recommended work–rest cycles. WBGT values obtained in the immediate work area are the most appropriate (assuming a properly functioning and calibrated WBGT instrument), because they will most accurately reflect actual conditions and result in more accurately predicted physiological responses. When personnel are wearing thick or impermeable uniforms, however, ambient WBGT values will usually not be a good predictor of the rapid onset of heat strain, because the ambient WBGT values in such circumstances will not accurately reflect conditions within the microclimate in the layer between the skin and inner layer of clothing. It is the microclimate in this layer that is most influential in characterizing the heat strain response rather than the ambient WBGT values. Ambient and skin–clothing microclimate values can differ substantially, because air movement in the skin–clothing microclimate layer is limited to air pumping from body movements. Occlusive clothing restricts the venting of microclimate air into the ambient air, thereby seriously reducing convective heat loss potential. In addition, the increased humidity in the microclimate skin–clothing layer has a positive feedback effect on increasing heat strain from reduced sweat evaporation rates.

The correlations between distant to local WBGT might be weak and nonstationary. They might be time-shifted, as the effect of clouds, wind, and other meteorological phenomena on spatial-temporal variations of WBGT traverse from one location to the other. However, variations in terrain features can be independently associated with substantial differences in WBGT readings. If only dry bulb temperatures are available, a model might require the user to measure or estimate ambient humidity, wind speed, and solar load. Such estimates will always be fraught with error. However, similar estimations are routinely made when exercising unguided judgment to decide how long to work when the weather is hot. In this respect, the model is no more susceptible to measurement inaccuracy than comparable unaided decision-making processes. Of course, ad hoc mental modeling is analogous to fuzzy logic algorithms, which are generally better suited than mathematical algorithms for processing imprecise inputs.[104] Fuzzy logic typically generates imprecise, but easy-to-comprehend useful recommendations or predictions. With fuzzy logic, precise measurements for the input variables are not necessary. If they are available, they must be "fuzzified" (ie, the precise input data must be appropriately categorized with respect to defined levels). In some instances, this "fuzzification" process can negate the effects of incorrectly specified initial values. Even though certain input variables must be estimated, model-generated predictions can still be more accurate than subjective opinions.

Some methodologies—such as Monte Carlo techniques to develop statistical probability boundaries, or the use of individual training sets with neural

TABLE 2-1

FAMILY OF THERMAL STRESS MONITORING SYSTEMS PROPOSED BY USARIEM

	Direct Model Applications					Model-based Guidance Documents	
System Name:	**PSM**	**MoHSM for PDA/BMIS-T**	**Heat Stress Monitor**	**Tactical Decision Aid**	**IWEDA**	**Area Guides**	**Heat Doctrine**
Models:	**ICDA**	**HSDA SCTM**	**HSDA**	**SCENARIO**	**HSDA SCTM**	**HSDA**	**All Models**
Users	Soldier information available through medical and command networks	Medic/small unit leader	Independent small unit	Company or battalion staff	Battalion or other field grade staff use and disseminate information	Individual soldier, small unit leadership	Corp/division command, and medical and logistics planners
Status	PSM under development	Testing and development	Tested as prototype (see text)	Not deployed	Weather product — upgrade in progress	Available for all soldiers via PHC	TB MED 507 doctrine based on WBGT—new models needed to improve guidance

BMIS-T: Battlefield Medical Information System–Tactical; HSDA: heat strain decision aid; ICDA: initial capability decision aid; IWEDA: Integrated Weather Effects Decision Aid; MoHSM: mobile heat stress monitor; PDA: personal digital assistant; PHC: US Army Public Health Command (formerly CHPPM [US Army Center for Health Promotion and Preventive Medicine]); PSM: (Warfighter) Physiological Status Monitor; TB MED: technical bulletin medical; USARIEM: US Army Research Institute of Environmental Medicine; WBGT: wet bulb globe temperature.

network models—can help address the issue of individual variability. Generally, however, models cannot predict precise responses for any specific individual. The predicted responses are mean responses for a group having the specified characteristics. Hence, models usually are not designed to handle the effects of natural variations within a group of individual characteristics or differences in clothing and workloads. A number of factors influence how this affects prediction accuracy.

The operational use of model-based decision aids should be incorporated into staff and medical services processes, as delineated in SOPs or guidance. Model-based products can then become ingrained into normal workflow and their use sanctioned in organizational publications. This helps ensure that decision aids will be used appropriately. Such references can also provide guidance for the proper use of model-based tools, including acceptable assumptions for nonmeasurable input variables.

There are two aspects to the USARIEM thermal modeling effort. The first, more scientific endeavor has been to develop a suite of thermal models, such as HSDA, SCENARIO, and SCTM. The second effort has been an attempt to transition the scientific knowledge to field applications. To that end, USARIEM has proposed a family of environmental health monitoring systems, as depicted in Table 2-1. This family of systems could help prevent heat injury or illness at the individual war fighter, small unit, and corps or division level. The plan, as conceptualized in Table 2-1, has not been achieved, but IWEDA incorporates the USARIEM thermal models as weather products on the system. SCENARIO has been developed as a PC-based analytical tool; and the simplified MoHSM does provide access to thermal models at the small unit or individual level. The heat stress monitor—because of a lack of a formal requirement, weight, cost, and bulk—was not accepted by the military, but the basic concept of the heat stress monitor continues to be pursued using other platforms, such as handheld weather instruments. These or similar modeling products should help provide the war fighter with a vital link to prevent thermal injury or illness.

SUMMARY

Models and simulations allow exploration of the likely consequences of high-risk situations or alternatives that are too dangerous, expensive, numerous, or time-consuming to actually test and evaluate. There are, however, some potential disadvantages in the use of models and simulations. The fidelity of models and simulations will always be limited to some extent. Transfer of training from model-based simulation to actual situations will never be perfect and, in some cases, there might be negative training transfer. The range of valid outputs will always be constrained to varying degrees by inherent assumptions. Model-based algorithms will become outdated as new information becomes available through experience or research. Also, the use of model-based products needs to be integrated into organizational practices, doctrine, and guidance. Models can be plagued by technical problems that are not readily apparent. For example, models that generate plausible outputs for certain ranges of input variables can have an algorithm that is partially or entirely incorrectly formulated. Thus, models should be verified as correct by subject matter experts. The structure and logic of a model might be correct, but biased because of the coefficients obtained from data in which test subjects or study conditions were not representative of the more general conditions for which model outputs are more commonly applied. The model results should be validated for the range of conditions and characteristics of populations for which the model will be considered applicable. Also, models almost always include simplifying assumptions. Therefore, results will be accurate insofar as the assumptions used in developing the model apply to the specific situation under consideration. A unit responsibility is that model assumptions or limits need to be disseminated. These qualifiers should be used as part of a checklist or other method to ensure that model limitations are understood and any restrictions are followed. This important step to ensure the appropriate use of models is often neglected or poorly done. Lastly, model development is often a lengthy and expensive process that frequently necessitates conducting research studies. A project management plan should be implemented in the early stages in the development of modeling applications that includes provisions for life-cycle product support.

Neglecting how the characteristics of prospective users and their corporate or military environments will affect model-based product acceptance and compliance with usage guidelines are common oversights in attempting to institutionalize the use of models and simulation-based applications. A comprehensive life-cycle project management approach for modeling and simulation products should be delineated, documented, and initiated during the early design phase. This type of long-term management approach for the development of biomedical models should also address and guide processes for identifying the technical competencies required for their effective use in operational settings. Provisions should also be made for product marketing and testing, document development and distribution, and product introduction and training. To maximize acceptance and integration of model-based applications into organizational processes, their use should be formally endorsed by leadership, starting with a formal, peer-reviewed requirements certification process based on MIL-STD 3022. Authority to modify doctrine and SOPs should be obtained from the organization's leadership and appropriate committees so that they support use of the new modeling or simulation product, because it adds capabilities or efficiencies useful to the organization or decreases operational risks and costs. If these administrative actions are not planned and accomplished, distributed model-based products that are fielded will largely be ignored and classified by intended users as the latest curiosity among a seemingly unending parade of unendorsed technological toys. The needs and potential usefulness of proposed model-based applications should be clearly and honestly identified and promulgated long before the product is ready for distribution. One practical reason for this is that individuals do not have the free time to learn new software or modify well-developed work processes to accommodate new, model-based applications that do not seem to offer significant or profitable new function, the use of which has not been explicitly mandated by leadership.

During military operations, the human costs of bad decisions can be serious. For example, miscalculation of the limitations of heat stress tolerance or water intake requirements in hot desert conditions, the difficulties and dangers to life and health of cold weather, or the susceptibility of personnel to incapacitating or lethal altitude illnesses can result in operational debacles, with the loss of not just a few personnel, but entire units. All military personnel should know the following facts without having to rely on elaborate mathematical models:

- that heat stress can kill;
- that running out of water, especially in hot desert areas, in hot desert areas can mean death from dehydration;
- that excessive lengthy immersion in cool-to-cold water, or exposure to cold, windy weather without adequate protective clothing and shelter can result in frostbite or eventual death from hypothermia; and
- that ascending to high altitudes too quickly can result in high rates of acute mountain sickness and death from rapidly progressive high-altitude pulmonary edema and high-altitude cerebral edema.

Common sense, foresight, analysis of observations and individual experiences, attention to practical details, and effective leadership have been and will continue to be of paramount importance in preventive medicine efforts during field operations. When environmental stress casualties occur, lapses in basic leadership and supervision, and failure to adequately consider and protect against the many potential adverse effects of conducting physically and psychologically demanding missions will almost always be at the root of the problem.

Models for predicting the effects of environmental strain are a modern refinement that can assist planners and preventive medicine personnel in detecting those circumstances in which apparent common sense or superficial qualitative evaluations might be fooled by effects that are more serious than expected. They can also be useful in identifying nonlinear effects that we cannot accurately sense, such as nearness to threshold of sudden performance decrements, or a sudden increase in heat stress casualty potential caused by seemingly slight changes in mission or environmental conditions. Model-based decision aids have been shown to be effective in refining plans for minimizing rates of environmental stress casualties that are already low, and even more so when attempting to maximize less visible—but operationally important—personnel effects, such as physiological reserve and performance potential. Environmental strain models broaden the capacity of planners to rapidly and accurately evaluate the effects of many combinations of environmental, mission, and personnel variables on the risks of environmental stress casualties.

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ATTACHMENT A: FINGER-COOLING MODEL

A generic, numerical finger-cooling model exhibiting simulated countercurrent arteriovenous heat exchange for predicting temperature response of digits to cold stress has also been developed at the US Army Research Institute of Environmental Medicine (USARIEM).[1] This type of model is of considerable interest because the fingers and toes are among the most vulnerable parts of the body to cold stress. Also, a whole-body thermoregulatory model can be formed by linking sets of cylindrical models for the extremities to a central body cylinder. At USARIEM, Shitzer and colleagues[2,3] developed a series of sophisticated models to predict the cooling and risk of frostbite in a single finger. The finger models included the effects of

- heat conduction,
- metabolic heat generation,
- convective heat transfer by blood perfusion,
- heat exchange between tissues and large blood vessels, and
- arteriovenous heat transfer.

The effects of handwear on heat transfer to the environment were also simulated using biophysical data from handwear insulation testing.[4]

The generic digit was modeled with four concentric compartments, from the center to the outer surface, consisting of core, muscle, fat, and skin, with heat flow along both the radial and axial directions. A system of distributed-parameter differential equations mathematically described the dynamics of heat balance within and between compartments and to the environment, metabolic heat generation, as well as countercurrent arteriovenous heat flow. Solutions for the time-dependent distribution of digit temperatures were obtained via use of the Thomas alternating direction method, which was extensively tested for convergence, accuracy, and stability. Interrelated parameters describing geometric tissue density, specific heat, basal metabolic rates and blood flow, and minimum nutritional blood flow were required for each compartment to complete the model description. Heat transfer coefficients, defining rates of heat transfer from skin to ambient air, were also identified for still air and moderate breeze for both bare and gloved fingers.

Shitzer and colleagues[2,3] provided an excellent example of how benchmark testing can be used in verifying stability and convergence of the software implementation of a complex thermoregulatory model. Through such testing, for example, they determined that, when the numerical algorithm used less than 20 nodes, results were a function of the number of nodes or temperature points within compartments. The complexity of the model has thus far limited its utility, but the countercurrent model serves as an excellent tool for illustrating the relative effects of countercurrent arteriovenous heat transfer on finger temperature patterns for various levels of ambient cold temperatures.

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ATTACHMENT B: WATER IMMERSION MODEL

Examples of immersion models are the lumped-parameter compartmental models developed for predicting body temperature responses to cold water immersion. For example, the US Army Research Institute of Environmental Medicine (USARIEM) developed SCTM, a six-segment (head, trunk, arm, hand, leg, and foot), whole-body cold immersion subprogram that included countercurrent arteriovenous heat transfer in the extremities.[1] The trunk and extremity segments were each modeled as solid cylinders containing four concentric compartments—(1) core, (2) muscle, (3) fat, and (4) skin—and associated blood flows. The head was modeled as a sphere having spherically concentric compartments. The passive intercompartmental heat transfer process was represented as a system of first-order, lumped-parameter differential equations. The lumped parameters represented compartment-specific values for thermal conductance, heat capacitance, blood flow, and metabolic rate. Simulation of the active vascular and thermogenic (shivering) processes added the necessary thermoregulatory feedback components to the cold water immersion model to make it dynamic and consistent with known cold stress-induced compensatory processes. The immersion model was validated against measured core temperature data for military test subjects immersed in 20°C and 24°C water. The model closely predicted core temperature changes in those conditions.

This model will be an excellent candidate for predicting safe cold water immersion times and will therefore be suitable for inclusion in various environmental stress analysis applications and decision aids. For example, this type of model could be incorporated into MyWIDA (My Weather Impacts Decision Aid), a PDA (personal digital assistant), or other handheld electronic device. The system or device would be capable of providing unit-level, site-specific, time-limit guidance for immersion in cool to cold water (eg, units that must consider routes that require wading across ravines or marches to achieve their objectives), as well as for heat stress evaluation and prevention in other settings.

If incorporated into MyWIDA,[2] this type of cold immersion model could provide contour overlays of recommended safe immersion times (based on reaching a selected core temperature limit) for training or operational areas where water immersion is a significant risk. This could then be used to direct units to avoid areas that pose an excessively high risk of immersion hypothermia or to recommend maximum exposure times that would be disseminated to the potentially affected units.

Another possible application of this type of tool is to assist in the planning of search-and-rescue operations. An example is the Probability of Survival Decision Aid (PSDA), based primarily on SCTM, that was developed for the US Coast Guard as a supplemental tool for search-and-rescue decision support.[3,4]

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